A Green and Pleasant Land? An Exploration of the Impact Associated with Planning Policy

by

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Thesis

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Contents

List of Tables

List of Figures

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Declarations

The work presented in this thesis is entirely original and my own work, except where acknowledged in the text. I confirm that this thesis has not been submitted in any previous application for any degree nor has it been published.

Abstract

The consumption of green space land due to urban development has evolved to become a key global concern. Whilst assumed to be a critical component in the control of land change, national planning policies have largely been omitted from analyses. Explorations of the effects associated with the transition between policy frameworks may therefore be considered a crucial element in advancing our understanding of the relationship.

This thesis applies novel statistical techniques to analyse the effects attributable to the introduction of the *Localism Act 2011* and *National Planning Policy Framework*, using green space as a primary indicator.

An initial analysis of green space loss using exploratory methods and *Change Point Detection* identified the existence of different structural patterns within the data, associable with the introduction of the revised policy framework. It further challenged extant concepts of the temporal dynamics of policy impact, suggesting evidence of increased land loss within 2 years.

Through *Interrupted Time Series Analysis* using *dynamic linear models* a policy intervention effect was obtained, which reported the policy to have led to a significant increased loss of green space, based upon both area and as a proportion of rates of residential development, intended to account for the underlying effect of economic drivers.

A final element of research evidenced a paradigmatic shift from a policy of urban containment to one permissive of expansion into the proximate rural periphery, using multiple datasets. Rates of green space and 'brownfield' development within urban boundaries were shown to have seen minimal effects under the revised framework. However, green space situated outside of said boundary was lost at an average rate 177% greater than under the preceding framework.

The research constitutes the first to provide robust empirical evidence that the policy reform impacted upon rates and patterns of land change. In so doing offering new insight with which to augment understanding of the functional dynamics of policy in the regulation of land use.

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Acronyms

AONB Area of Outstanding Natural Beauty.

ARIMA Autoregressive Integrated Moving Average.

ARMA Autoregressive Moving Average.

CPRE Campaign to Protect Rural England.

DCLG Department for Communities and Local Government.

DLM Dynamic Linear Model.

EVI Enhanced Vegetation Index.

GLM Generalized Linear Model.

GLS Generalized Least Squares.

Ha Hectare.

ITS Interrupted Time Series.

Km Kilometre.

LAA Local Authority Area.

LSOA Lower Super Output Area.

m Metres.

MAE Mean Absolute Error.

MHCLG Ministry of Housing Communities and Local Government.

NDVI Normalized Difference Vegetation Index.

NPPF National Planning Policy Framework.

ODPM Office of the Deputy Prime Minister.

OLS Ordinary Least Squares Regression.

ONS Office for National Statistics.

OS Ordnance Survey.

PPG Planning Policy Guidance.

PPS Planning Policy Statement.

RMSE Root Mean Squared Error.

CHAPTER 1

Introduction:

The Enduring Idyll?

"*Meanwhile, at social Industry's command,*
How quick, how vast an increase. From the germ,
Of some poor hamlet, rapidly produced,
Here a huge town, continuous and compact,
Hiding the face of the earth for leagues - and there,
Where not habitation stood before,
Abodes of men irregularly massed,
Like trees in forests - spread through spacious tracts.
O'er which the smoke of unremitting fires,
Hangs permanent, and plentiful as wreaths,
Of vapour glittering in the morning sun,
And, whereso'er the traveller turns his steps,
He sees the barren wilderness erased,
Or disappearing."

The Excursion
Wordsworth (1820)

1.1 Introduction

Throughout the world, the Twentieth and Twenty First Centuries have evidenced a rapid demographic transition from predominantly rural to urban living (Galea et al., 2005). By 2008 over half of the global population were recorded as resident in urban settlements (Budruk et al., 2009). As a consequence of the resultant increased demand for additional accommodation, infrastructure and resources, allied to the finite availability of land, significant pressure has been placed upon undeveloped natural areas, such as green space

(Budruk et al., 2009; Folke et al., 1997). This developmental pressure upon land is expected to continue to intensify as the increase in urban populations shows no abatement (Patra et al., 2018). The extent of urban settlements is predicted to triple by 2030, consuming an additional 1.2 million km^2 of predominantly natural surfaces, in order to accommodate an extra 1.35 billion people globally (Biello, 2012; Seto et al., 2012).

In parallel, natural and previously undeveloped land has increasingly become recognised as integral to environmental sustainability (European Commission, 2016), based upon the provision of ecosystem services, which reflect '*the benefits human populations derive, directly or indirectly from ecosystem functions*' (Costanza et al., 1997). These incorporate *supporting* services, which reflect biotic and abiotic processes (such as photosynthesis) (Thaiutsa et al., 2008); *regulating* services, which comprise a diverse range of regulatory functions (such as the amelioration of air quality (Bolund and Hunhammar, 1999)); *provisioning* services, which relate to resources obtained from the ecosystem (such as agricultural production (Power, 2010)); and *cultural services*, which constitute immaterial benefits (such as positive effects upon physical and mental health (Lee and Maheswaran, 2011)).

Although the extent of undeveloped land is influenced by environmental factors and agricultural intensification (Ståhle, 2010), the most significant threat is often portrayed as development of built environment (Haaland and van Den Bosch, 2015). The loss of derived ecosystem services associated with the expansion of urban environments is therefore considered to represent one of the most significant challenges to sustainability (OECD, 2018), formally recognised as an international policy priority (European Commission, 2016). Of particular concern is land which represents the periphery between urban and rural usage (Benito et al., 2010).

Whilst patterns of urban induced land use change are understood to be influenced by interrelated socio-economic, political, natural, technological and cultural forces (Bürgi et al., 2005), the role of planing policy in both a regulatory and facilitative function is considered crucial (Hersperger et al., 2018). Consequently, planning systems must be utilised efficiently in order to ensure patterns of sustainable development which retain natural and semi-natural land (Egoh et al., 2008).

However, the development of an understanding of the relationship between policy and land change has only recently become established as a research aim (Hersperger et al., 2018). Primarily advanced through new forms of digital data, which provide the opportunity to monitor and analyse land change over a more consistent period (Juliev et al., 2019), allied to the entrenchment of evidence and outcome based policy within structures of governance (Gertler et al., 2016; Head, 2008; White and Masset, 2018).

A growing research basis has evolved with a focus upon the exploration of the relative conceptual role of spatial planning as a driver of urban induced land change (Hersperger et al., 2018). However, empirical analyses constitute a sparse field (Kasraian et al., 2019), generally restricted to targeted policy provisions (such as conservation measures (Verburg et al., 2004)), with limited focus upon comparative policy impacts (Mu et al., 2016). Correspondingly, evaluation of planning policy has tended to concentrate upon outputs (such as policy documents and plan performance) rather than outcomes (such as intended and unintended land use change) (Shahab et al., 2019). In order to address this issue it is contended research must focus upon establishing robust empirical evidence of the causal impact of policy upon landscapes (Bürgi et al., 2005; Morrison and Pearce, 2000; Plieninger et al., 2016).

Particular focus is placed upon examples drawn from policies implemented in the context of stable landscapes, where existing measures may be considered factors in the regulation of change (Bürgi et al., 2005; Plieninger et al., 2016). Having previously been explored in relation to the United Kingdom (Dallimer et al., 2011), the subsequent adoption of a revised policy framework provides a pertinent example through which to explore cognate effects.

1.1.1 Planning Redefined

Upon election in 2010, the Conservative led coalition government espoused radical reform of the previous planning system as one of the core tenets of its policy agenda (Cabinet Office, 2010). Embedded into the nebulous concept of '*localism*' (Haughton and Allmendinger, 2013) and promoted as the means by which to stimulate economic recovery in the aftermath of the global financial crisis (DCLG, 2011), the revisions were intended to vastly simplify planning procedure with an enforced "*presumption in favour of sustainable* *development*" (DCLG, 2011) at its heart.

Initially through the *Localism Act 2011* and subsequently the *National Planning Policy Framework* [*NPPF*] (2012) a system defined by over a thousand pages of separate, detailed planning policy guidance was replaced by a single, minimally prescriptive 65 page document (Fisher et al., 2013).

A number of retrospective analyses have since contended the revised system was constrained by an inherent path dependency (Raco, 2014), as a result of which it merely reflected a continuation of the prevailing neo-liberal principles, which had dominated British politics since the 1980s (Davoudi, 2011; Haughton and Allmendinger, 2013; Raco, 2014; Slade, 2018). However, throughout the consultation process undertaken prior to enactment, vociferous opposition was raised by myriad non-governmental organisations, including environmental stake-holders (such as the Campaign to Protect Rural England, Countryside Alliance and Chartered Institution of Water and Environmental Management), whom perceived it to represent a significantly increased threat to the natural environment (Sibley-Esposito, 2014).

Consequently, the revised planning framework under the *NPPF* rapidly became portrayed in the media as a "*builders' charter*" (Wright, 2012), which threatened the cultural inviolability of the rural idyll (Harrison and Clifford, 2016). Despite conciliatory amendments to the policy (Sibley-Esposito, 2014), concerns persisted that it represented a fundamental ideological shift from urban containment to sprawl (Harrison and Clifford, 2016), ultimately driven by vested economic interests (Tait and Inch, 2016).

This discourse in relation to the developmental threat to natural land has been augmented by limited empirical analysis to date (CPRE, 2018). Whilst as an example of the transition between two differing approaches to planning policy within a highly urbanised country (Dallimer et al., 2011), the examination of this change can provide additional insight in regards to a previously minimally explored relationship with land change.

1.2 Research Aim and Objectives

This thesis was designed to develop a novel empirical understanding of the developmental impacts of the *Localism Act 2011* and *National Planning Policy Framework* upon the prevalence and patterns of undeveloped green space land. It is intended to contribute to the nascent development of a body of knowledge that improves understanding of how national level planning policy may directly or indirectly impact upon land use change. Whilst the outcomes can be used to inform future *ex ante* evaluation and predictive modelling in order to support the policy cycle.

To achieve this aim the following research objectives were adopted:

1. Derive a methodologically consistent, spatio-temporal green space loss dataset incorporating periods prior to and after the implementation of the policy reforms;
2. Apply geospatial data analytic methods to assess the evidence of a structural change in relation to the rate of development occurring on green space and whether such is associated with the introduction of the *Localism Act 2011* and *National Planning Policy Framework*;
3. Empirically investigate the effect of the policy reforms upon the rate of development upon green space;
4. Empirically investigate whether the policy reforms have altered spatial patterns of development from a focus upon containment within extant urban boundaries to the facilitation of urban expansion.

1.3 Research Questions and Thesis Contributions

The thesis can be understood to address three key research questions, which cumulatively account for the first empirical analysis of the impact of the revised policy upon green space land. They additionally, suggest the potential of data-driven analytical methods as a means through which to estimate the effects attributable to national planning policy, such that similar approaches could be employed to assess the impact of policies upon different urban areas.

Jointly, the three elements of the thesis [chapters 4, 5 and 6] incorporate aspects of the research priorities identified as imperative to exploring the underlying forces which determine land change (Bürgi et al., 2005; Plieninger et al., 2016), within the context of planning policy. The data upon which analyses are founded augments the growing body to utilise alternatives to prevailing remote sensed resources (Plieninger et al., 2016) and presents the efficacy of vector maps. Analyses enable the identification of trajectories of land change over time (Bürgi et al., 2005), providing new insights in regards to the temporal dynamics which underpin the relationship between national policy and green space loss. Conceptually, the research investigates the impact of changes associated with regulatory functions, which are intended to counteract the influence of other underlying drivers (Bürgi et al., 2005; Plieninger et al., 2016), potentially enabling the isolation of a single factor. Additionally, two robust methods are deployed as means through which to discern and quantify a causal relationship (Bürgi et al., 2005; Morrison and Pearce, 2000; Plieninger et al., 2016).

Research Question 1: Has the area of green space which was subject to development evidenced alteration in rates which could be associated with the adoption of the *Localism Act 2011* and *National Planning Policy Framework (2012)*?

Following the enactment and introduction of the revised planning system concern was raised by conservation organisations that it would lead to increased loss of green space (Sibley-Esposito, 2014). This perspective was disputed by government, whom outlined its increased provision for the protection of publicly valued green space (DCLG, 2011) and the retention of a 'plan-led' approach, in which Local Authorities would be able to control patterns of development (Rhodes, 2011). However, this discourse has been augmented by limited *ex post facto* empirical analysis (CPRE, 2018), which could provide novel insights in regards to the specific effects of policy change and a more general understanding of the dynamic relationship between policy and land change.

Contribution 1: Through the novel application of a systematic, evidence based method of data analysis the research provided the first empirical indication of the effect of the adoption of the revised policy regime on the developmental pressure upon green space. The applied methodology suggests the potential expansion of *change point detection* as a means through which to empirically test the existence of policy interventions based upon temporal shifts in land change data. The research further addresses the need for analysis that advances the conceptual model of the relationship between policy and land change through examination of temporal dynamics.

Research Question 2: What impact have the *Localism Act 2011* and *National Planning Policy Framework* had upon the total area of green space subject to development?

The majority of quantitative analyses have focused upon assessment of the relative contribution of policy to land change, rather than as an isolated determinant (Hersperger et al., 2018). Where focused upon the identification of policy impact, predominant methods have been restricted to 'pretest-posttest' designs or linear regression (Dallimer et al., 2011), which are considered subject to risks related to internal validity (Dimitrov and Rumrill Jr, 2003; St. Clair et al., 2014). Within other fields of policy impact research where a randomised controlled trial is not feasible, quasi-experimental methods have been established as robust alternatives (McDowall et al., 2019). However, such have been subject of limited use in regards to land use change (Ramachandra, 2019) and not previously been applied to planning policy.

Contribution 2: This research employs a previously unused approach to statistical analyses, which enabled the establishment of a quantified intervention effect deemed likely to be attributable to the adoption of the revised planning framework. Consequently, it can be considered to improve understanding of the dynamic relationship between changes to policy and urban induced land change, addressing the demand for robust methods of causal inference.

Research Question 3: Do analyses of rates of development upon green space offer insights in regards to the extent to which the revised planning framework can be characterised as enabling urban expansion?

It has previously been established that the planning system is crucial in the containment of development to extant urban boundaries (Mu et al., 2016). Whilst, National 'Green Belt' policies within the UK have been evidenced to have been highly effective in this regard (Baing, 2010), the role of wider deregulatory policy provisions have not been analysed (Pauleit et al., 2005). A supposition was posited that the revised framework would increase developmental pressure upon land outside of existing urban boundaries (CPRE, 2018). However, there has been no definitive empirical analysis undertaken to test this hypothesis.

Contribution 3: The final contribution of this thesis investigated the impact of policy change upon the spatial pattern of development in relation to existing urban boundaries, using methods consistent with established policy impact evaluation. It evidenced an association between the adoption of a policy which could be considered broadly more permissive of development and a rapid alteration to the distribution of development. This validates existing research (Dallimer et al., 2011; Mu et al., 2016) and informs the wider development of theories relating to the role of policy in regards to patterns of urban expansion.

1.4 Thesis Structure

In **chapter 2** core theoretical, conceptual and methodologically relevant literature were reviewed to establish the academic foundation upon which subsequent research was founded. As this research can be considered to reside at the confluence of green space, land change science and policy impact analysis fields, each were explored from theoretical and methodological perspectives.

Chapter 3 addressed the methodological approaches which underpin each section of the thesis. It outlines the development of the primary green space loss dataset, which was utilised in all subsequent analyses. Original data sources and relevant temporal ranges were described. The minimum change identification method was summarised. A distinct sampling methodology was set out, including relevant foundational data sources. Finally derived data sets were presented in advance of the methods of data analysis utilised in **chapters 4**, **5** and **6**.

The first contribution chapter (4) sought to augment current knowledge of the relationship between national level policy and land change through the novel application of quantitative methods in regards to a previously unexplored policy. By means of simple summary statistics and *change point detection* it suggested a relationship between the transition to a new policy regime and an increased rate of development upon green space land. In so doing, the research presented *change point detection* as a reliable means through which to identify a structural shift in data in response to policy, which could be applied in regards to myriad policy areas.

Extending this initial analysis, **chapter 5** empirically established a quantifiable intervention effect associated with the previously identified policy change. The research tested the use of a robust methodology, used extensively in alternative areas of public policy, which could address issues related to causal inference considered to have limited previous studies. *Interrupted time series* analysis enabled the role of policy in the regulation of land use to be conceptualised in a novel manner. It further offered an empirical evidence base for anecdotal concerns raised in regards to the revised policy framework.

To expand upon both prior contribution chapters, the research undertaken in **chapter 6** introduced *Interrupted Time Series* analysis as a robust method through which to investigate patterns of development within 'Green Belts' and the rural fringe. The role of national policy in facilitating the expansion of urban areas into peri-urban green space had not previously been addressed using such causal inference models. The research suggested the revision of national policy had led to a significant increase in the area of land lost to development outside of extant urban boundaries. It emphasised the important role played by policy in ensuring the pursuit of compact city principles.

Finally, **chapters 7** and **8** reflected upon the cumulative contribution of the research to the advancement of a conceptual model of the relationship between planning policy and land change. Implications of the research for urban science and policy making were discussed. Limitations associated with the existing work were subsequently used to inform the development of a future research model, which should accordingly seek to build upon this work as a foundation.

CHAPTER 2

Literature Review

What Would William Morris Say?

"*King Street was gone, and the highway ran through wide sunny meadows and garden-like tillage. The Creek, which we crossed at once, had been rescued from its culvert, and as we went over its pretty bridge we saw its waters, yet swollen by the tide, covered with gay boats of different sizes. There were houses about, some on the road, some amongst the fields with pleasant lanes leading down to them, and each surrounded by a teeming garden.*"

News From Nowhere
Morris (1897)

2.1 Introduction

The potential impact associated with different national policy approaches to the regulation of land change is a crucial consideration as pressure upon the rural-urban fringe increases (European Commission, 2016). This study, which seeks to address the need for exploratory research based upon *ex post facto* impact evaluation (Shahab et al., 2019), using the controversial transition to the *National Planning Policy Framework* in the United Kingdom (Sibley-Esposito, 2014), can be considered to reside at the confluence of green space, land change and policy analysis fields.

Accordingly, both the importance of and benefits associated with the retention of green space land are outlined within the context of an ecosystem services approach. Contemporary concepts related to the identification of factors that are deemed to facilitate and regulate land change are described. Whilst quantitative approaches to the estimation of policy effects are examined. Additionally, relevant contextual detail is provided in relation to the operation of the planning system within the United Kingdom and the interpretation of the legal provisions within the revised planning framework, which are considered to have led to an increased threat of development.

2.2 Key Definitions

2.2.1 Drivers

Within comparable land change literature, the concept of driving forces (commonly referred to as '*drivers*'), collectively incorporating the myriad "*forces that cause observed land change*" (Bürgi et al., 2005) frame theoretical and experimental understanding (Thelin, 2014). Implicitly, 'drivers' assume a causal relationship with land change, but do not describe the causal mechanisms by which said change occurs (Meyfroidt, 2016).

Although both the identification of and effects associated with 'drivers' have been adopted as the core focus of research (Hersperger et al., 2010), the term is commonly used to encompass a wide range of processes operating at different scales (Thelin, 2014). Discussed jointly, 'drivers' are commonly deemed to include both underlying and proximate causes of change [refer to 2.5], considered as elements of a fundamental 'causal chain' (Meyfroidt, 2016), in which they interact within the context of a complex system (Thelin, 2014). Underlying drivers are generally categorised as either anthropogenic or environmental factors which result in a subsequent process producing a physical change to land use or land cover (Lambin et al., 2001; Ostwald et al., 2009; Plieninger et al., 2016; Turner et al., 2007). For example, a National Planning Policy acts as an underlying driver, determining developmental priorities (Kasraian et al., 2019), which is filtered through local development plans and the actions of individual actors representing the proximate causes of recorded physical land change (Hersperger et al., 2018).

Whilst recognised as elements of complex adaptive systems (Hersperger et al., 2018), analysis of 'drivers' as single factors used to explain transitions between land use represent a fundamental assumption within land change science (Ostwald et al., 2009). Accordingly 'drivers' are explicitly interpreted as features in regards to which there is evidence of casual association, but not necessarily sufficient evidence through which to definitively establish a casual effect or extrapolate as to the mechanisms underpinning such (Meyfroidt, 2016). In line with prior research, this thesis defines 'drivers' as both underlying and proximate causes of land change, including "*political, economic, cultural, technological and natural*" processes (Bürgi et al., 2005). With the 'driver' subject to analysis within this research representing the transition between the revised policy framework (in the form of the *Localism Act 2011* and *National Planning Policy Framework*) and the preceding policy.

2.2.2 Causal Inference

A number of key assumptions underpin the causal inferences derived throughout this thesis. From a statistical stand point the adopted methods are fundamentally predicated upon the concept of single causality (Trafimow, 2017), related to an identifiable and isolable driver of land change (Morrison and Pearce, 2000). In so doing they are largely consistent with precedent land change research (Dallimer et al., 2011; Ganser and Williams, 2007; Ganser, 2008; Mu et al., 2016), which often assume a simple, positivistic, linear relationship between drivers and land change (Hersperger et al., 2010).

Common to 'Single *Interrupted Time Series Analysis*' the research undertaken assumes association based upon a counterfactual theory of causation (Baicker and Svoronos, 2019), in which the recorded outcome is compared to a circumstance in which the subject intervention did not occur (Bavli, 2019). Despite said method reportedly performing comparably to a *Randomised Controlled Trial* within an epidemiological context (Fretheim et al., 2013), counterfactual causation is fundamentally dependent upon the capacity to control for extraneous variables (Linden, 2017), rendering it less reliable in relation to complex systems (HM Treasury, 2020a). However, it is contended to remain a robust quantitative approach in circumstances in which the context remains relatively stable and where largely exploratory analysis is intended to estimate impact.

Both planning policy and land change dynamics are considered likely to reflect complex adaptive systems (Hersperger et al., 2018; Kasraian et al., 2019). Whilst the applied methods accounted for the most highly cited confounding variable (in the form of economic influences) (Morrison and

Pearce, 2000), allowed for a high degree of counterfactual uncertainty (Brodersen et al., 2015), and post-analytical consideration was given to plausible alternatives (Roemmele et al., 2011) reported causal relationships are restricted to association (Young et al., 2014). The outlined causal inference is ultimately dependent upon the stability of extraneous drivers, assuming that policy represented the single factor regulating the complex interacting forces recognised as driving land change (including individual actors). Whilst statistically, this approach may be deemed to offer a more robust estimation of causal association than in comparable land change research (Dallimer et al., 2011), the absence of formal methods accounting for underlying complexity must be born in mind (Trafimow, 2017). Within the context of *Interrupted Time Series Analysis* the outlined approach offers robust causal association (Bernal et al., 2017), but cannot be understood to identify causality between the the introduction of the revised policy framework and land change. In light of the inherent complexity associated with the research, the potential for extraneous variables to account for or contribute towards the outcome is high (HM Treasury, 2020a), with their omission from the statistical methodology and potential for concurrent effects to bias inference crucial (Linden, 2017).

2.2.3 Green Space

Despite an increasing prominence within research and ubiquity beyond, green space can be considered to represent an ill defined term, subject to contrasting organisational, academic and social interpretations (Taylor and Hochuli, 2017). Conceptually, Taylor and Hochuli (2017) suggest relevant definitions could loosely be categorised as either designations of all ‘natural’ space (including bodies of water) or specifically vegetated surfaces associated with urban environments.

Commonly, public accessibility represents a key feature of the definitions (Barbosa et al., 2007; Bertram and Rehdanz, 2015; Maas et al., 2006), particularly in regards to urban environments (Lachowycz and Jones, 2013), upon which the majority of research has been focused (Taylor and Hochuli, 2017). However, this should be understood to be directly attributable to the research hypotheses, in which focus is upon social interaction with such spaces (for example in relation to mental and physical health effects (Lee and Maheswaran, 2011)).

Whilst definitions associated with environmental amelioration or ecology may be more specific (such as the urban tree canopy (Bolund and Hunhammar, 1999)), where applied to the overarching principle of ecosystem services they generally include all vegetative land cover (Swanwick et al., 2003; Taylor and Hochuli, 2017).

Within the context of spatial planning and concomitant planning policy the term remains subject to differing interpretations, ranging from any vegetated land cover (Dallimer et al., 2011) to publicly accessible defined examples with minimum area criteria (Moseley et al., 2013). In general the adopted definitions are inexorably bound to the methodological approach undertaken (Taylor and Hochuli, 2017). For example, in Senanayake et al. (2013) '*green spaces*' were identified using a *Normalised Difference Vegetation Index* [*NDVI*] derived from satellite imagery and therefore could only be categorised as any surface with vegetation. Whereas due to the utilisation of detailed vector data Moseley et al. (2013) were able to restrict green space to 14 defined publicly accessible typologies.

For research related to the planning framework within the United Kingdom additional complexities must be addressed. Under the commonly applied definitions of green space within research, three distinct types of land may be discerned which are subject to different regulation and must be addressed accordingly (Adams and Watkins, 2002).

2.2.3.1 Greenfield

Although not a statutorily designated term, land which has not previously been subject to development is commonly termed 'greenfield' (Cullingworth and Nadin, 2003). There are no specific provisions within planning policy for such (Adams and Watkins, 2002), but it should be considered synonymous with green space within research.

2.2.3.2 Brownfield

Whereas land on which there has previously been developed form is referred to colloquially as 'brownfield' (Adams and Watkins, 2002). This is not to say that 'brownfield' sites may not be dominated by vegetative cover (Bardos et al., 2016) or recognised as ecologically and socially productive spaces (Macadam and Bairner, 2012). Such land can better be understood as a designation through which to reduce urban sprawl (Cullingworth and Nadin, 2003), aimed at the constraint of the built environment to its previous footprint (Adams and Watkins, 2002).

2.2.3.3 Green Belt

In addition to the outlined, exists the concept of 'Green belt', which represents a designated planning term relating to the control of urban development (Cullingworth and Nadin, 2003). Conventionally, 'Green belt' land surrounds an urban settlement, with the defined intention to;

- *check the unrestricted sprawl of large built-up areas;*
- *prevent neighbouring towns merging into one another;*
- *assist in safeguarding the countryside from encroachment;*
- *preserve the setting and special character of historic towns; and*
- *assist in urban regeneration, by encouraging the recycling of derelict and other urban land.*

(Garton and Barton, 2019)

Having been included within planning policy since 1955, the 'Green belt' is subject to specific development regulation (Amati and Taylor, 2010).

For the purpose of this research a definition of green space was adopted which incorporated all vegetative land cover upon which it could be identified there had not previously been development. Accordingly, it incorporated the nine urban land categories discerned by Bell et al. (2007) (representing '*parks and gardens; natural and semi-natural spaces; green corridors; outdoor sports facilities; amenity greens spaces; provision for children and young people; allotments, community gardens and urban farms; cemeteries, disused churchyards and other burial grounds; and public space*'), allied to rural equivalents based upon Alcock et al. (2015) (primarily agricultural land).

2.3 Green Space Benefits

The importance of both urban and rural undeveloped green space has become an increasing focus of multi-disciplinary research (Wolff et al., 2020). Whilst predominantly concerned with urban environments (Burgess et al., 1988; Wolf, 2004; Caspersen et al., 2006; Bertram and Rehdanz, 2015), jointly the benefits and values associated additionally with rural spaces can be framed within the concept of *ecosystem services* (Young, 2010). The outlined framework relates green space to "*the benefits human populations derive, directly or indirectly from ecosystem functions*" (Costanza et al., 1997). Relevant functions are structured under four categories of *provisioning*, *regulating*, *cultural* and *supporting* services (Bolund and Hunhammar, 1999), with the network of urban and rural '*green spaces*' considered as a single ecosystem (Young, 2010).

Supporting services can be understood to reflect the biotic and abiotic processes which underpin other functions (Bolund and Hunhammar, 1999) (such as photosynthesis (Thaiutsa et al., 2008) and nutrient cycling (Bolund and Hunhammar, 1999)). In an urban context relevant services are provided by natural vegetative surfaces, such as street trees (Salmond et al., 2016). Whilst it has also been evidenced areas of rural grassland contribute to core nutrient cycling functions (Schroter-Schlaack et al., 2016). Additionally, the combined, interconnected network of '*green spaces*' represent the foundation of habitat provision for a range of species of flora and fauna (Swanwick et al., 2003), with even small areas of land acting as transitional natural corridors enabling movement (Dunnett et al., 2002).

The extent to which a green space provides a foundational habitat has been evidenced to be dependent upon both area and quality (Swanwick et al., 2003). However, whilst large monoculture fields have been shown to provide more limited species diversity (Srivastava et al., 1996) than some incidental vegetated urban spaces (Threlfall et al., 2017), they represent a key element of a functional green network (De Montis et al., 2016), often bordered by hedgerows which serve as both transitional refuges (Lecq et al., 2017) and dedicated habitats (Ernoult and Alard, 2011).

Both relevant urban and rural green space are also considered to contribute towards key *regulating services* (Schroter-Schlaack et al., 2016), such as the amelioration of air quality (Bolund and Hunhammar, 1999), reduction of surface temperature (Swanwick et al., 2003), sequestration of Carbon Dioxide (Fryd et al., 2011) and regulation of surface water (Swanwick et al., 2003).

Although determined by physical structure (Vieira et al., 2018), vegetative cover has been evidenced to both permanently and temporarily reduce the prevalence of air pollution (Bolund and Hunhammar, 1999). Pollution particulate matter can either be absorbed and metabolised within the microbiome (Weyens et al., 2015) or retained upon leaf surfaces (Mitchell et al., 2010). Ameliorating effects have been evidenced locally in relation to the presence of urban parks and street trees (Bolund and Hunhammar, 1999), whilst at a larger scale a forested area situated at the boundary of an urban conurbation has been shown to reduce pollution across the entire city (Baumgardner et al., 2012).

Similar effects have been associated with the regulation of surface temperatures (Swanwick et al., 2003), with the increased evapotranspiration attributable to '*green spaces*' estimated to reduce temperatures by between 2°C and 5°C at a local level (Bolund and Hunhammar, 1999). Having evidenced a reduction in temperature of 0.1°C (Maheng et al., 2019) the conversion of any such area to man made surfaces is understood to have a significant effect. Although areas of green space situated outside of cities have minimal impact upon the urban heat island effect their retention is considered crucial to wider climate control (Trenberth, 2004).

Additionally, areas of undeveloped green space have been evidenced to contribute towards the regulation of the climate through the sequestration of Carbon Dioxide (CO_2) (Fryd et al., 2011). This occurs both directly through photosynthesis (Raven and Karley, 2006) and subsequently as a result of storage in soil aggregates (Lal, 2004). However, both the type of vegetative cover and land management practices are deemed to be crucial to this process (Bolund and Hunhammar, 1999), with certain grazing practices evidenced to emit excess Carbon, primarily related to biotic functions (Ostle et al., 2009). Conversely, a single Hectare of dense vegetated green space can be considered to sequester around one tonne of atmospheric CO_2 (Bolund and Hunhammar, 1999). Thus, the benefits attributable to green space are more complex, but the prevalence of such surfaces is generally characterised as beneficial to climatic conditions (Lal, 2004).

Primarily due to the greater permeability of soil substrates related to green space, such land cover is highly influential in regards to hydrological flow

(Bolund and Hunhammar, 1999). Areas of green space have been associated with reduced surface run-off in comparison to man made surfaces (Swanwick et al., 2003). Notably, research into impacts upon urban environments have suggested that lower densities of sealed surfaces offer greater regulation of water flow than the retention of bounding areas (Gill et al., 2007). Therefore, it could be inferred ensuring developmental pressure was reduced within extant urban boundaries is the most critical aspect to flood protection (Farrugia et al., 2013). However, the contribution of all forms of green space as permeable surfaces are highlighted as integral to building hydrological resilience (Schroter-Schlaack et al., 2016).

The *provisioning services* derived from green space include fibre, food, fuel, genetic resources and water (Young, 2010). Through both urban allotments (Swanwick et al., 2003) and large areas of rural agricultural land one of the core functions of green space in the United Kingdom pertains to food production (Amati and Taylor, 2010). Designated 'Green Belt' land is fundamental to such, with 16% of the 1,063,645 Hectares used for agriculture registered as being of the highest quality (Grades 1 and 2) (CPRE, 2010). Based upon a study of 29 cities Folke et al. (1997) estimated that in order for an urban conurbation to have access to sufficient resources to be considered sustainable it would need to be bounded by an area of undeveloped land between 565 and 1,130 times greater than itself. Thus, the area of green space could be deemed essential.

Direct societal benefits associated with green space are broadly categorised under *cultural services*, which include positive effects upon physical and mental health (Lee and Maheswaran, 2011) and the improvement of social cohesion (Jennings and Bamkole, 2019). Whilst a strong evidential base has evolved during the last two decades to support the ameliorating effects upon health related to both access to and sensory interaction with green space (Van Dillen et al., 2012), particularly in regards to mental health and well being (Wood et al., 2017), it is dominated by urban studies relating to accessibility (Lee and Maheswaran, 2011). Primarily attributable to complex rights in regards to access, negligible research has been undertaken in relation to rural spaces (Schroter-Schlaack et al., 2016). However, with evidence suggestive of attributes associated with rural spaces alleviating stress (Grahn and Stigsdotter, 2010), such spaces can be conceived of as contributing to core *cultural services*.

Whilst it is acknowledged a number of the key benefits and values associated with green space are more heavily influenced by quality rather than area (Wood et al., 2018), the potential impacts associated with significant loss of such spaces represent established research and political priorities (Young et al., 1994), facilitated through analysis of land change (Turner et al., 2007).

2.4 Land Change Science

Key Definitions

Land Cover Change: Within research the term *land cover change* refers to the physical conversion of a terrestrial surface to an alternative land form (such as the change from vegetated to artificial surfaces) (Yadav et al., 2019).

Land Use Change: *Land use change* is defined as the alteration to the anthropogenic use derived from the land (such as the change from arable to pastoral agriculture) (McConnell, 2015)

Although distinct terms, land cover and land use change are commonly explored concurrently (Juliev et al., 2019) and have evolved as a key environmental priority during the last two decades (Friedl and Brodley, 1997; Hersperger et al., 2010; Lambin et al., 2001; Turner et al., 2007), recognised as such by inter-governmental agencies (including the *European Environment Agency* (Manakos and Braun, 2014) and *Organisation for Economic Co-operation and Development* (OECD, 2018)).

Land change science can be conducted based upon data derived from maps, official resources (such as governmental statistics (MHCLG, 2019d)), field surveys, Cadastral records and social surveys (Harrison et al., 2002; Plieninger et al., 2016). In order for research to be deemed practicable at the large geographic extent required to derive generalisable inference, research tends to rely upon remote sensed data, pre-classified digital maps or records of official statistics (Plieninger et al., 2016).

In one approach, research may be based upon pre-classified vector data commonly produced by official agencies (such as *Ordnance Survey in the UK*) (Bibby, 2009). Due to such data typically being subject to licence it is rarely used within a research context (Dennis et al., 2018), but forms the basis of governmental monitoring (Bibby and Brindley, 2013). Land change can reliably be understood as any polygon, in regards to which relevant classification criteria have altered between two time periods (Bibby and Brindley, 2013). As a result of additional classification detail, such vector data is considered to provide insight into thematic land use change in a way that is not easily replicable in regards to remote sensed imagery (Dennis et al., 2018). However, relevant data sets are subject to delays between the occurrence and recording of change (Ordnance Survey, 2009), which must be incorporated into analysis (Orford and Radcliffe, 2007), whilst they cannot be used to detect vegetative cover quality.

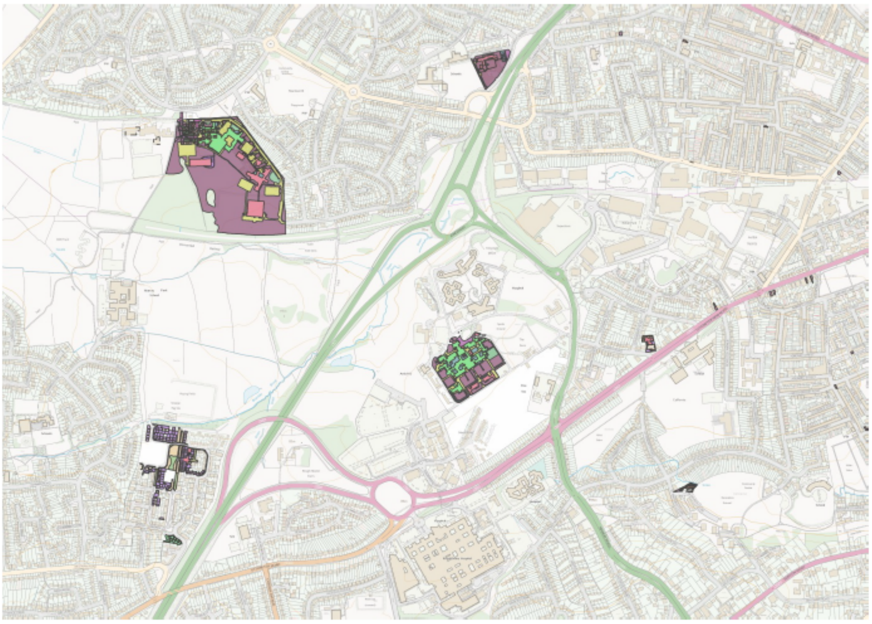

Figure 2.1: Source: DCLG (2015a):
Example thematic land use change derived from vector data (*OS Mastermap* ®).

Each alternative data source offers different advantages and issues, which must be assessed against the intentions of analysis (Lu et al., 2004). As mentioned previously, remote sensed data allows for extensive geographical coverage, at a range of resolutions, which is theoretically accessible at regular intervals (around every 15 days in the case of the *Landsat* programme (Zhu and Woodcock, 2014)) (Fonji and Taff, 2014). Accordingly it can provide a consistent historical record often difficult to access in alternative formats (Zomeni et al., 2008) and has been utilised extensively in myriad studies to successfully monitor large scale land cover change (Turner et al., 2007).

However, obtaining a consistent temporal range can be significantly hindered by cloud cover obstruction (Fonji and Taff, 2014). Sano et al. (2010) identified maximum cloud cover of 10% as optimal, which can limit the viability of a large number of images (Shen et al., 2016), particularly in relation to examples such as the United Kingdom (Grey et al., 2003). In part this issue may account for the large and inconsistent time intervals often applied in relevant research. For example, in a study intended to compare urban expansion in regards to 50 global cities between 1985 and 2010, Bagan and Yamagata (2014) were only able to access data relating to 1995 and 2000 for Glasgow (UK) and 1985 and 2000 for Cape Town (South Africa) due to inhibitory cloud cover. This issue also commonly restricts the number of research observations, as a consequence of which appropriate inferential modelling techniques may be limited (Zhang et al., 2011).

Whilst satellite data can offer resolutions of 30cm (Shermeyer and Van Etten, 2019), the most commonly used available resources (such as *Landsat Thematic Mapper*) tend to range between 20m and 30m (Li et al., 2017b) and as a result can be contended to be too coarse for the identification of some types of change (Fonji and Taff, 2014). Despite such concerns the 30m x 30m resolution of *Landsat Thematic Mapper* has been deemed adequate to enable identification of large scale land cover change in a range of research (Vittek et al., 2014). As long ago as 1994 the U.S. Geological Survey utilised data from *Landsat Thematic Mapper* as a medium through which to identify different crop type coverage (Raymond and McFarlane, 1994) supporting the notion that its resolution would be capable of being used to identify more significant land use change, such as from green space to developed artificial land (Kerr and Ostrovsky, 2003). However, where seeking to categorise small area changes, such medium resolution satellite data may remain inadequate (Fisher et al., 2018). This could be a prominent issue in regards to the identification of urban infill developments (Huang et al., 2017).

Arguably of greater significance to the suitability of satellite data is degree of contrast between land types (Fonji and Taff, 2014; Horning and DuBroff, 2004). As an example, the occurrence of deforestation for the purpose of intensive agriculture can be reliably identified (Souza Jr et al., 2013), based upon the succession from dense forest to sparse vegetative land cover [figure 2.2]. However, where land cover is more temporally heterogeneous, such as the transition from building to 'brownfield' higher resolution imagery is required (Banzhaf and Netzband, 2004).

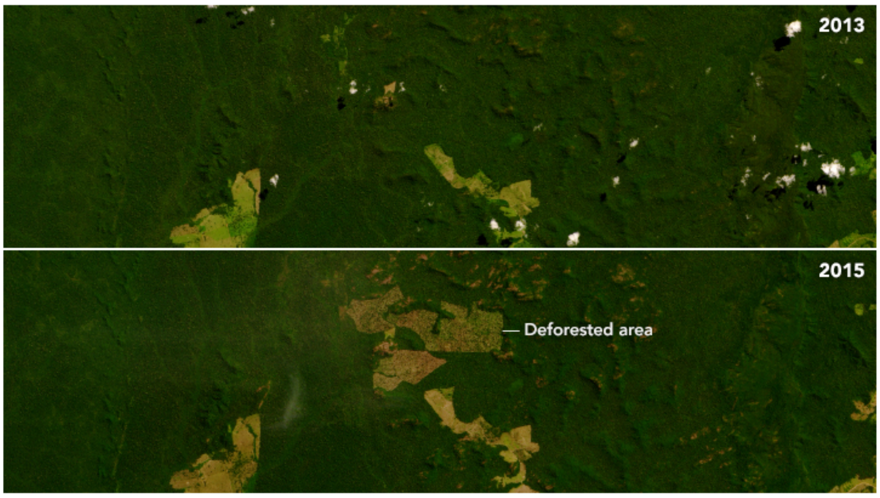

Figure 2.2: Source: NASA (2019):
Landsat image reflecting an area of deforestation within the Amazon obtained through 30m resolution data.

Furthermore, although satellite imagery using vegetation indices can provide estimates of the quality of vegetative land cover (Wulder et al., 2012), used in isolation they are less reliable for the identification of land use (Fonji and Taff, 2014).

Conversely, vector resources provide data at a high degree of granularity (Orford and Radcliffe, 2007), which enables both the identification of small scale change and increased accuracy. Significantly more advanced land use detail can be obtained through such resources, enabling the differentiation between types of green space, which may be similar in regards to vegetative cover (Moseley et al., 2013). Openly accessible governmental records further offer data at consistent time intervals, unaffected by climatic conditions (Fuchs et al., 2015).

However, due to the complexity of the data significant storage and processing resources are required, generally relying upon management through relational database systems (Yao and Li, 2018) [figure 2.3]. Consequently, it is largely impractical to undertake analysis using vector data for large geographic extents (such as an entire country). Allied to which, the development of analytical algorithms is complicated (Yao and Li, 2018). As a result the use of vector data has been minimal in land change research (Smith et al., 2007).

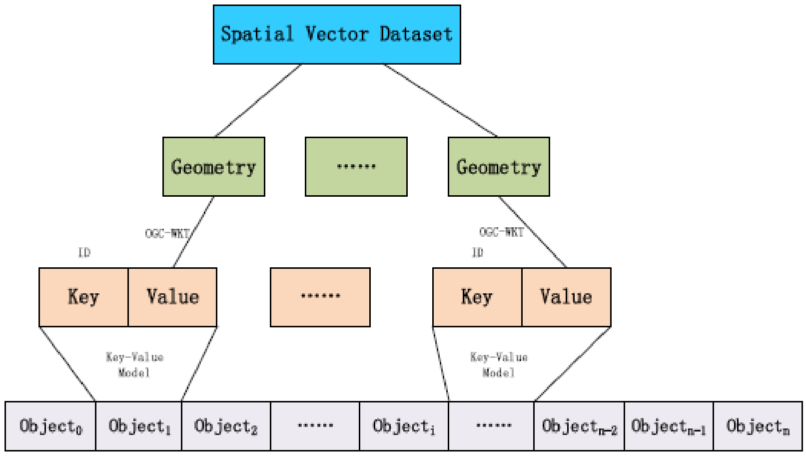

Figure 2.3: Source: Yao and Li (2018):
Example data structure related to a relational database.

2.5 Identifying Drivers

The primary function of land change science has evolved from a focus upon simply monitoring patterns of change (Hersperger et al., 2018) towards the development of conceptual models that advance understanding of the causes which drive the conversion of landscapes (Garcia-Martin et al., 2020). Relevant driving forces are conceived of as either proximate or underlying (sometimes referred to as distal) factors (Lambin et al., 2001; Ostwald et al., 2009; Plieninger et al., 2016; Turner et al., 2007). A proximate driver can be understood to reflect a direct, physical cause of land change (Ostwald et al., 2009), primarily in the form of local level anthropogenic activities (Plieninger et al., 2016), such as the expansion of urban areas (Turner et al., 2007). Whereas, underlying drivers constitute the processes that generate such physical changes (for example population dynamics (Plieninger et al., 2016)).

Hersperger et al. (2010) outlined four theory of change models through which to conceptualise the relationships between land change and those factors considered likely to influence such [referred to as *driving forces*]. In the form of the '*Driving Force - Land Change*', '*Driving Force - Actor - Land Change*', '*Driving Force/Actor - Land Change*' and '*Actor - Land Change*' models (Hersperger et al., 2010) (Hersperger et al., 2018).

The first model ['*Driving Force - Actor*'], upon which the majority of land change research is based (Hersperger et al., 2010) assumes a direct, linear relationship between the occurrence of a physical change and existence of a driving force. Such as, between increased household income and the conversion of larger areas of agricultural land to urban (Alig et al., 2004). Whilst contended to be causally weak due to its presumption of single causality (Bunge, 2017), it has been applied as the prevailing model in a large range of land science research undertaken at different spatial scales (Hersperger et al., 2010), including that upon which this thesis is founded (Dallimer et al., 2011).

The '*Driving Force - Actor - Land Change*' model assumes a slightly more complex relationship in which a driving force influences an actor's decisions and subsequently the land change they produce (Hersperger et al., 2010). For example, changes to land taxation policies were considered to have been evidenced to have caused agricultural land owners to convert crop lands to grazing (Thapa and Rasul, 2006). The practical application of the outlined model to research tends to rely upon a mixed methods approach (Hersperger et al., 2010), with land change data based upon existing physical resources, but the role of actors determined through surveys.

Although similar to the above, the '*Driving Force/Actor - Land Change*' model is based upon the understanding that driving forces have a complex relationship with actors (allowing for feedback loops) and combine to induce land change (Hersperger et al., 2010). In example, Gennaio et al. (2009) analysed the influence of local development plans upon relevant organisational actors and their subsequent decisions in regards to the revision of succeeding local development plans, which were subsequently related to resultant physical land use change. Whilst embracing ideas of complexity and offering descriptive insights in regards to the relationship between actors and drivers, the use of methods built upon this model have been limited and deemed largely inappropriate at large geographic scales (Hersperger et al., 2010).

Whilst acknowledging the existence of driving forces, the '*Actor - Land*

Change' model places the decisions of actors as the core cause of land change (Hersperger et al., 2010). The aim of research within the context of this model is to uncover the role of individual decision making upon individual parcels of land. Similarly to the '*Driving Force - Land Change*' model, relevant methods assume single causality with complex relationships between multiple actors not commonly addressed as a result of practical issues in obtaining data (Hersperger et al., 2010).

Empirical methods through which to statistically explore the relationship between land change and these driving forces (both proximate and underlying) have been developed (Plieninger et al., 2016). The primary of which, is designed to identify the relative roles of different drivers upon individual instances of land change (Hersperger et al., 2018), to support both predictive and explanatory modelling (Millington et al., 2007).

Commonly, this approach is founded upon regression techniques (primarily multinomial logistic regression), in which land change is a dependent variable and potential drivers (for instance elevation, land shape, distance to infrastructure or land ownership) represent independent variables within the model (Corbelle-Rico et al., 2015). Ostensibly, the statistical significance associated with each independent variable (driving force) represents a quantification of the difference between models including different variable profiles (Martínez et al., 2011).

In a simple explanatory example, Millington et al. (2007) examined the influence of 12 environmental and socio-economic drivers using a Multinomial Logistic Regression model. The relative statistical significance of each hypothesised driver was derived from a hierarchical partitioning approach based upon comparison of fit between all models that included the driver and those from which it was omitted. Analysis suggested the proximity to alternative land use, potential yield, mean farmer age and percentage of population employed in agriculture were the key drivers in the transition from agriculture to scrub land. However, results were ultimately inconclusive and offered limited means by which to interpret effects associated with individual variables (Millington et al., 2007).

Whilst the outlined methods have been evidenced to support predictive models

(Verburg et al., 2004), the extent to which they offer understanding of the processes which facilitate or regulate change remains limited (Plieninger et al., 2016). Where proximate drivers have been robustly quantified within models, the links to underlying factors are less well established (Plieninger et al., 2016). This issue may in part account for the limited use of quantitative analyses within relevant literature, which is dominated by qualitative methods (Hersperger et al., 2018; Plieninger et al., 2016).

The most widely cited research relating to underlying drivers of land change was conducted by Brandt et al. (1999), in which a simple descriptive analytical framework is outlined as a means to establish correlation between drivers and land use at different spatial scales (Bürgi et al., 2005). Five core underlying drivers of land change were identified based upon transitions in agricultural land, categorised as "*political*, *economic*, *cultural*, *technological* and *natural factors*". The outlined drivers have evolved as the primary accepted framework and have influenced the majority of subsequent research (Plieninger et al., 2016). Whilst similar "*policy*, *economic*, *social* and *biophysical*" driving forces were associated with urban induced land use change, allied to "*proximate interactions*" (which refers to spatial autocorrelation between new and existing land types) (Nuissl and Siedentop, 2020).

Research has suggested that underlying and proximate drivers cannot be considered in isolation (van Vliet et al., 2016), with all five underlying factors identified as cumulatively contributing towards patterns of land change (Plieninger et al., 2016). However, research has been largely unable to address issues of causal inference, with new approaches which focus upon processes contended to represent research priorities (Bürgi et al., 2005; Hersperger et al., 2018; Plieninger et al., 2016). Bürgi et al. (2005) identified seven research areas required to advance the development of conceptual models relating to driving forces of land change. These could be interpreted as;

- comparative analysis of land change in regards to areas that cross administrative borders;
- analysis of regulatory functions, which restrict land change;
- the development of methods and data which account for inherently dynamic landscape change;
- analysis relating to temporal rates of change;

- the development of models related to factors that promote the location of development;
- the existence of precursory change that may signify subsequent land change; and
- the advancement of experimental methods through which to actively test the causal relationships between hypothesised drivers and types of land change.

Based upon a systematic literature review, Plieninger et al. (2016) built upon the outlined priorities, firstly identifying the need to "*[expand] the scope of studies to include underrepresented countries, biogeographic regions, and land-use systems and to also consider drivers of landscape stability*". The prioritisation of stable landscapes was contended to be critical as they characterise the majority of developed nations; offer valuable insights in regards to the role of regulatory functions, which can be used to mitigate against driving forces of change; and provide historical repositories. This can be considered in conjunction with the recommendation to analyse factors which restrict development (Bürgi et al., 2005).

Plieninger et al. (2016) further advocated "*[t]he deployment of more robust tools and methods to quantitatively assess the causalities of landscape change, while maintaining the holistic character of landscape studies*". This concept links into the recommendation for methods to be developed, which can test for causal relationships between drivers and land change as exploratory functions (Bürgi et al., 2005).

Whilst, the adoption of "*[l]ong term studies that go beyond the use of satellite imagery, considering diverse types of data on landscape change*", can be understood to relate to the need to account for the underlying natural dynamics of land change processes (Bürgi et al., 2005).

Additionally, primarily based upon the conceptualisation of models proposed by Hersperger et al. (2010), separate recommendations were made to develop "*conceptual clarity with regard to the role and identification of actors vs. driving forces of landscape change*" and the "*design of multi-scale studies that* *consider distal relations between actors, drivers, and patterns of landscape change*" (Plieninger et al., 2016).

2.5.1 Spatial Scale

Urban analytic research is commonly considered subject to potential bias as a result of the '*modifiable areal unit problem*', which recognises analytical outcomes are dependent upon the spatial scale and size at which relevant data is aggregated (Wong, 2004). For example, Openshaw and Rao (1995) evidenced that by adopting different spatial scales correlations between employment status and access to personal transport ranged from -1 to +1. With reported correlations generally considered more likely in circumstances where aggregation occurs at a larger scale (Lee and Kemp, 2000).

Whilst it is identified that the optimal spatial unit for any analysis is dependent upon both the dependent variable and geographic extent of interest (Flowerdew, 2011), the majority of research focused upon the United Kingdom is aggregated to '*Ward*' or '*Enumeration District Area*' level (Tranmer and Steel, 2001; Lloyd, 2016). It is contended the adoption of said scale is largely associable with population level analysis derived from census methodologies (Lloyd, 2016).

The '*modifiable areal unit problem*' is not generally addressed within the context of land change research, in which the primary focus is upon the identification of a spatial scale at which changes would be evident in available data (Kozak and Szwagrzyk, 2016). Such is therefore primarily conducted using urban boundaries, which are considered to act as a sample reflecting national scale outcomes (Dallimer et al., 2011). Therefore, discussion of relevant research needs to be understood as potentially producing different analytical outcomes based upon the adoption of different spatial scales either amounting to different sample areas or subsamples of previously utilised spatial units (Lloyd, 2016).

2.6 The Relationship Between Planning Policy and Land Change

Despite an implicit theoretical presumption that planning policy represents one of the key underlying factors determining and regulating urban land change (Couclelis, 2005), there has been relatively little research dedicated to the explicit examination of such (Hersperger et al., 2018; Li et al., 2017a). One contention posited by Briassoulis (2009) suggests this can be accounted for by the situation of research at the intersection between social geography, in which concepts of space are considered to be uncertain and land change science, which seeks to identify causal links. Alternatively, it can be associated with issues related to wider research of underlying drivers (Plieninger et al., 2016).

However, examples of qualitative and quantitative analyses can be identified, mostly relating to local or regional case studies (Hersperger et al., 2018). Relatively few operate at a national scale (Kasraian et al., 2019), reflecting limitations associated with data and processing resources (Fonji and Taff, 2014). The majority utilise between 3 (Dallimer et al., 2011; Pagliarin, 2018; Warren et al., 2011) and 5 time intervals (Kasraian et al., 2019). Whilst, relevant data sources ranged from digitised historic maps (Bieling et al., 2013) to satellite imagery (Mu et al., 2016).

Qualitative methods can broadly be categorised into two paradigms. The first of which considers policy as one of a number of potential factors influencing general trends in land change (Hersperger et al., 2018). For example, Bieling et al. (2013) identified the percentage of an area to undergo change from undeveloped to developed form in regards to three case study localities, based upon 3 time intervals. Due to data access each locality was analysed at slightly different temporal ranges (Lauterach: 1820 - 1913, 1913 - 1952, 1952 - 2009; Unterlenningen: 1828 - 1905, 1905 - 1955, 1955 - 2009 ; Zainingen: 1824 - 1901, 1901 - 1958 and 1958 to 2009). Based upon the derived land change data, historical records were analysed for proximate explanatory drivers, such as population shifts or the introduction of regulatory frameworks. Said records were deemed to suggest the transition from marginal grasslands and heath to developed form were partially attributable to policy, but offered negligible means of identifying its individual role.

The second qualitative approach attempts to distil the role of policy as an individual factor relative to other drivers and actors (Hersperger et al., 2018). In Hersperger and Bürgi (2010), types of land change were assigned drivers based upon document analysis and expert interview. For example, '*loss of orchard due to new construction*' would be assigned '*Cantonal transportation and infrastructure policy*' as one of the drivers inducing change. Subsequent categorisation enabled each assigned driving force to be associated with underlying drivers (conforming to the 5 types identified by Bürgi et al. (2005)), from which political factors could be separately analysed. This suggested that political factors (restricted to policies, spatial planning, international agreements and political actors) were a driver in regards to around a quarter of all land change. Land use planning was identified as a significant factor in regards to urbanisation in each time interval. The outlined results were deemed to highlight the crucial role played by planning policies in the direction of development. However, analysis of the effects associated with relevant policies were deemed to require more robust examination.

Whilst such qualitative methods were advanced as a key exploratory stage in the analysis of driving forces (Bürgi et al., 2005; Hersperger et al., 2018), the development of conceptual models relating to the role of policy were contended to be dependent upon data-driven analyses (Morrison and Pearce, 2000).

To date, quantitative alternatives reflect a small field of research (Hersperger et al., 2018), in part attributable to the contention that they are dependent upon a reductive interpretation of policy (McNeill et al., 2014). The main method applied is based upon the use of regression models to discern the relative role of policies in relation to individual changes in land use (Hu and Lo, 2007; Kasraian et al., 2019; Liu et al., 2011) (replicating the standard approach referred to in section 2.5).

Kasraian et al. (2019), adopted a generalized linear model in which the dependent variable (land change) was modelled against independent variables which included three distinct policy provisions coded using binary variables, in conjunction with infrastructure proximity (Hersperger et al., 2018). The three policies subject to analysis could all be categorised as broadly regulatory (Galle et al., 1997), with the most long standing ('*Green Heart*' policy) intended to conserve a large expanse of undeveloped land (Kühn, 2003), the second ('*Growth Centre*' policy) implemented to direct suburban expansion (Verburg et al., 2004) and the third ('*Vinex*' policy) to contain development within existing urban boundaries (Galle et al., 1997). Land change focused upon urbanization and was identified as any 500m by 500m cell, in which the proportion of urban land cover changed between two time intervals [figure 2.4].

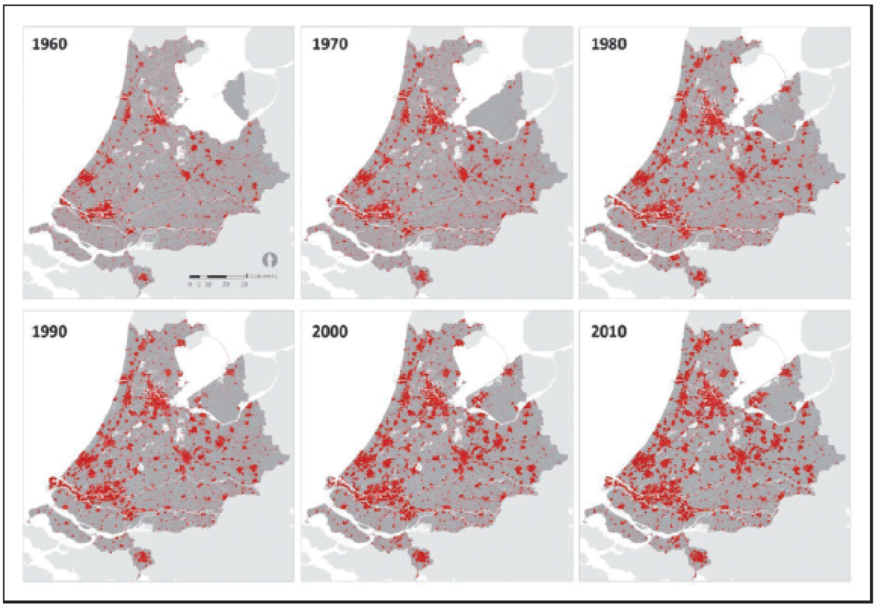

Figure 2.4: Source: Kasraian et al. (2019): recorded urbanisation during study period.

At decadal intervals, land change data was interpreted as highly supportive of the significant role of each policy in guiding development. For example, between 1960 and 2000, cells that would be subject to the provisions of the '*Vinex*' policy were evidenced as less likely than other cells to undergo urbanization. However, in 2010 relevant cells were 64.3% more likely to be subject to development. This both intimated as to the role of policy in directing development (Kasraian et al., 2019) and suggested a significant temporal lag in the policy, introduced in 1990, causing change.

The '*Growth Centre*' policy introduced in 1960 evidenced an increase in the likelihood of a relevant cell being subject to development (relative to other cells) of 10.6% in 1970, 19.2% in 1980, 19.7% in 1990, 18.7% in 2000 and 17.9% in 2010. In so doing the research addressed the need for analysis relating to rates of change (Bürgi et al., 2005). However, at decadal intervals, isolating the influence of policy could be considered problematic. Whilst the original resolution (25m) at which change was identified may underestimate the influence of small scale developmental loss (Fonji and Taff, 2014).

There has been limited research based upon the association between policy and general trends of development, particularly at a national level (Hersperger et al., 2018). Based upon comparison of the total area dedicated to each land type at 5 time intervals, Mu et al. (2016) reported that national policy measures, which relaxed regulatory constraint, were a significant factor in the conversion of large areas of agriculture to urban form.

Within the context of the United Kingdom, policy measures have been the subject of two primary research studies. Dallimer et al. (2011) empirically investigated the extent to which the reform of the national policy agenda in 2000, with a defined focus upon densification, had increased the loss of urban green space to development. To do so it measured the change which occurred in the total area of green space across 13 cities identified as the largest based upon population. Whilst both geographically dispersed [figure 2.5] and reflective of a range of socio-economic profiles (Dallimer et al., 2011), the restriction of the sample to just 13 cities which may be subject to similar external influences (Cullingworth and Nadin, 2003) rendered generalisation difficult.

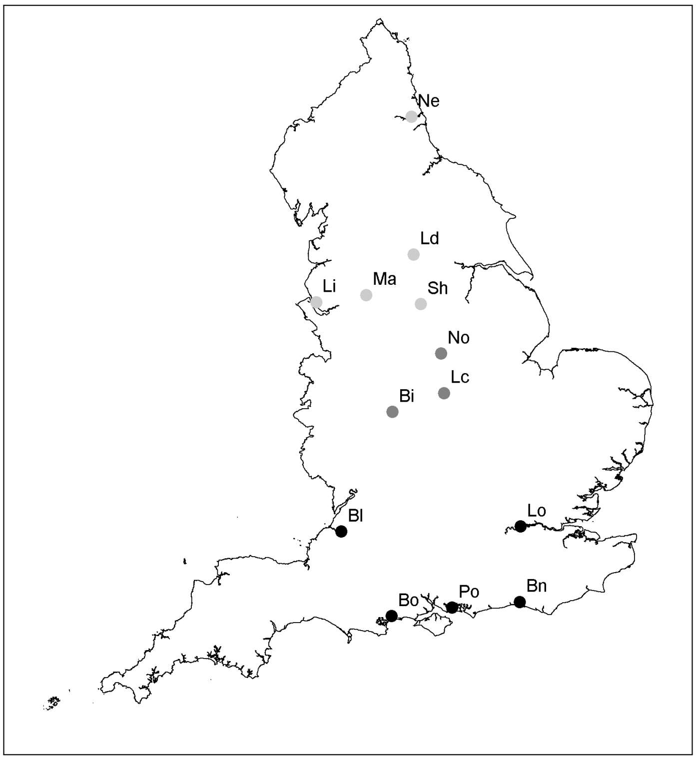

Figure 2.5: Source: Dallimer et al. (2011)
Location of 13 sample cities identified in indicative Southern (black), Central (mid-grey) and Northern (light-grey) regions.

Methodologically, the research adopted two distinct approaches. The primary data sources for the initial approach were medium resolution (30m x 30m) satellite images obtained for each of the sample cities in 1991, 2001 and 2006 (Dallimer et al., 2011). The extent of built environment and green space within the urban boundaries at each time interval were identified using a supervised classification technique based upon the *Maximum Likelihood Estimation* [*MLE*] algorithm and were subsequently compared. For each city an average change in green space area was derived per annum for the two intervals (1991 to 2001 and 2001 to 2006).

In the second method, data represented 250m x 250m resolution, pre-processed Enhanced Vegetation Index [*EVI*] images obtained at 16 days intervals between 2000 and 2008. In order to account for the potentially confounding effects of external variables, (such as climatic conditions) upon the data, the research used a metric based upon the difference between the mean EVI values obtained within the defined urban boundary and within a 2 to 5km ‘rural’ buffer surrounding said boundary [equation 2.1].

$$EVIdif = EVI_{in} - EVI_{out} \tag{2.1}$$

Where $EVIdif$ is the difference metric, EVI_{in} represents the average annual EVI score relating to the pixels within an urban boundary and EVI_{out} is the annual EVI score for the pixels contained within an indicative rural buffer.

The results from the initial analysis evidenced nine of the thirteen cities underwent an increase in green space area prior to the policy (1991 to 2001), but recorded reductions in area during the period after (2001 to 2006). These results can be considered in parallel with evidence presented by Ganser and Williams (2007), which suggested that a smaller proportion of 'greenfield' land [outside of urban boundaries] was subject to development in 2002 than 1992. Both indicate the occurrence of a change in the type of land cover subject to development.

Based upon linear regression, the EVI difference metric utilised in the second method evidenced that cumulatively, the area within the urban boundary was becoming less green relative to the surrounding rural buffer. This was interpreted as suggestive of the influence of infill development, which created pressure upon undeveloped spaces within the urban boundary (Dallimer et al., 2011). However, this temporal effect was only reliably evidenced in regards to 3 sample cities.

Dallimer et al. (2011) provided a conceptual basis for policy impact analysis through general trends in land change data, which directly addressed the lack of *ex post facto* research (Shahab et al., 2019) and can be considered to represent the core contribution to the field (Haaland and van Den Bosch, 2015). The responsive dynamic relationship between policy and land change outlined by Dallimer et al. (2011) contrasted with the continuing legacy of prior regimes noted by Kasraian et al. (2019), but may be attributable to the underlying differences of the policy approaches (discretionary and zoning) (Oxley et al., 2009).

Significantly, statistical analyses in Dallimer et al. (2011) were primarily based upon '*pretest - posttest*' principles or linear regression, considered less reliable than alternatives where seeking to establish causal inference (Shadish et al., 2002), particularly in regards to policy analysis (Morrison and Pearce, 2000). Additionally, the research did not explicitly suggest that it accounted for the potential lag between policy implementation and it's effect upon the planning system associated with the application and approval of development Lichfields (2016). However, the modelled post-policy trend may be considered to mitigate against confounding bias.

The results evidenced by Dallimer et al. (2011) were broadly consistent with studies based upon governmental records of rates relating to the numbers of new homes built on both previously developed and undeveloped land (Ganser and Williams, 2007). For three time intervals (1992, 2003 and 2006) the proportion of development which occurred on previously developed land increased from 46% to 56% and finally 58%. These results were largely supportive of the influential role of targeted regulatory policies in the containment of development (Baing, 2010). However, they also intimated as to the potential for unintended consequences of policies, suggesting the imposition of targets had led to an increase in total development and net loss of green space.

Interpreted holistically, the outcomes reported in each research project indicated the material role of regulatory policy in the containment of development. This can be deemed analogous with the work conducted by Kasraian et al. (2019) and may suggest the effectiveness of strongly regulated development within diverse policy settings (Oxley et al., 2009). Whilst both Colantoni et al. (2016) and Fiorini et al. (2019) reported from the study of the spatial growth patterns of informal settlements that in the absence of any regulation areas would expand outwards. Both were based upon single settlement studies within the vicinity of large urban conurbations in countries with similar economic profiles. The significant role of economic drivers were reported in each study, but demographic change was only relevant in one. Such informal and unapproved developments offer limited insight alone in regards to the effect associated with regulatory function and suggested the need for analysis to be undertaken based upon differing degrees of deregulatory systems (Colantoni et al., 2016). Both Dallimer et al. (2011) and Kasraian et al. (2019) also recommended the need to conduct future research in relation to the two broadly deregulatory policy frameworks, which were introduced subsequent to the research period in each.

Both the qualitative and quantitative approaches adopted in a variety of research suggest policy is a strong contributory factor in relation to rates and patterns of development. It was noted in Morrison and Pearce (2000) that research was required in which the focus shifted from the association of policy with land change to the use of land change as an indicator of policy effects. In pursuance of this, methods were needed with which to explore the impacts associated with policy in isolation, based upon a prediction of the outcomes that would have been evidenced without the policy. In regards to which practical examples of a clear transition between policies were deemed to be necessary. Whilst, in light of the ineluctable need for systems to balance environmental protection with population pressures, Dallimer et al. (2011) highlighted the absence of analyses which sought to explore the impacts associated with different policy approaches to urban containment.

2.7 Policy Evaluation

From the systems thinking perspective commonly adopted in policy practice, evaluation is considered to encompass administrative functions, outputs and outcomes (Vedung, 2017), which can be framed around three categories of question ("*descriptive*", "*normative*" and "*cause-and-effect*") (Imas and Rist, 2009). Accordingly, scholars such as Vedung (2017) draw a clear distinction between evaluation, which incorporates the holistic process, including design and implementation (McCall et al., 2016); and impact evaluations (Lan and Yin, 2017), intended to explore the effect associated with a targeted intervention (Venetoklis, 2002).

In contrast to the largely reductionist, positivistic frameworks commonly applied in impact evaluations (Haynes, 2008), prevailing methods in policy evaluation incorporate underlying concepts of complexity science (Sanderson, 2002). Based upon an understanding that most policy interventions are implemented within complex adaptive systems (Haynes, 2008) or are themselves complex systems (Shiell et al., 2008), approaches including *agent-based models*, *causal loop diagrams*, *qualitative comparative analysis*, and *qualitative case studies* have been incorporated into evaluation process (Barbrook-Johnson et al., 2021; HM Treasury, 2020a). Crucial to such is a foundation upon a theory of change model (HM Treasury, 2020b), with the adoption of appropriate methods dependent upon the characteristics of the system under analysis (Haynes, 2008).

Commonly a combination of multiple approaches may be utilised to ensure robust inference founded upon myriad sources of data and information (Sanderson, 2002). Relevant methodological approaches can be categorised as '*participatory*', in which they are subject to real time feedback from actors; '*theory based*', which focus upon the causal mechanisms; '*configurational case-based*', through which to derive the combination and relative roles of factors which produce the subject effect; '*counterfactual based*', which utilise experimental techniques to quantify effects; '*statistical association*', which employ exploratory techniques to support causal inference; and '*synthesis designs*', that bring together results from multiple analyses (HM Treasury, 2020a). The prevailing complexity based approaches to evaluation represent an epistemological perspective intended to derive effects, causal mechanisms and values associated with a policy intervention (Sanderson, 2000). Accordingly, impact evaluation can be considered a single constituent of this approach, alone insufficient to account for evaluation of complex policy systems, but forming an element of an holistic approach to such (Haynes, 2008).

2.7.1 Quantitative Analysis of Policy Impacts

Impact evaluations (sometimes referred to as Impact Assessments or Outcome Based Evaluation [*OBE*] (Schalock, 2001)) have a single focus upon the causal effects attributable to a defined policy intervention (Gertler et al., 2016). They are considered a vital component to the prevailing evidence and outcome based policy agenda (Gertler et al., 2016; Head, 2008; White and Masset, 2018), contributing to accountability and learning (HM Treasury, 2020b), which can subsequently inform future *ex ante* evaluation (Mergaert and Minto, 2015) and predictive modelling (Gilbert et al., 2018).

The most commonly adopted methods of impact evaluation are framed around experimental or quasi-experimental approaches (Ferraro, 2009). The foundation of which are based upon the capacity to analyse the outcome achieved with the intervention having occurred against the outcome which would've occurred without the intervention (referred to as the '*counterfactual*') (Gertler et al., 2016) [figure 2.6].

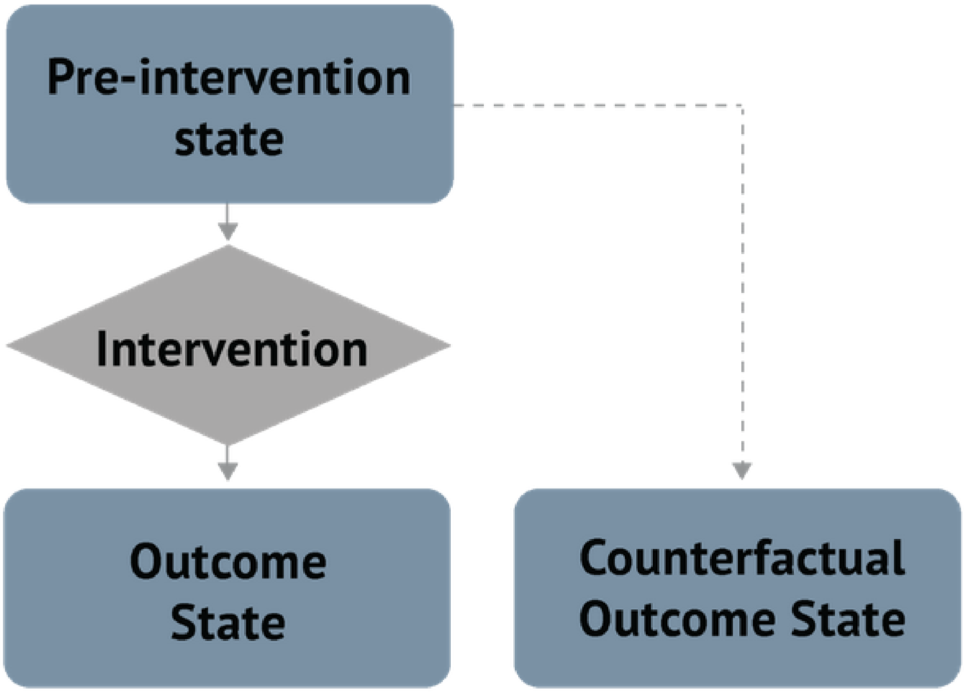

Figure 2.6: Source: *Mendelsohn and Ghali (2019)*
Conceptual Framework for Policy Intervention Impact Analysis.

The most prominently advocated method is based upon the replication of experimental concepts using *Randomised Controlled Trials* [*RCT*] (Haynes et al., 2012), in which different interventions are assigned to defined representative sample, study groups (which may consist of individuals or regions) and compared against a relevant control (Pearce and Raman, 2014). Ostensibly, an intervention effect can therefore be represented by the difference between the group who received the intervention and the control (Haynes et al., 2012).

At a practical level the use of a controlled design is precluded in regards to retrospective analysis (Kontopantelis et al., 2015) and population-wide implementation (Bernal et al., 2017). In such circumstances quasi-experimental alternatives can be considered (HM Treasury, 2020b).

2.7.2 Interrupted Time Series Analysis

Interrupted Time Series [*ITS*] analysis represents a strong, quasi-experimental alternative to the use of Randomised Controlled Trials (Biglan et al., 2000; Wagner et al., 2002), advocated as a reliable and statistically robust means through which to derive causal inference in regards to the relationship between an intervention and recorded outcomes (McDowall and McCleary, 2014; Bernal et al., 2017). It is deemed to be of particular value in regards to the retrospective analysis of secondary data derived from a single group without feasible access to a relevant control (Linden and Yarnold, 2016). A scenario in which policy intervention must often be assessed due to population-wide implementation (Bernal et al., 2017) or as a consequence of ethical and practical limitations (Wagner et al., 2002).

Accordingly, iterations of the *ITS* method have been applied to policy impact analysis in a variety of fields (Britt et al., 1996), most prominently in regards to public health (Murry et al., 1993; Ansari et al., 2003; Bloor et al., 2003; Andersson et al., 2006; Dowding et al., 2011; Serumaga et al., 2011; Penfold and Zhang, 2013; Bernal et al., 2017). Examples of its use include the assessment of the direct impact of a national advertising campaign upon rates of road traffic collisions (Murry et al., 1993), the implementation of a ban on smoking in public areas upon cardiac event admission rates (Barone-Adesi et al., 2011) and the adoption of new regulations relating to the prescription of antibiotics on rates of its use (Ansari et al., 2003).

Having primarily evolved through public health (Bernal et al., 2017), the method has since been applied to research within the spheres of education (Wong et al., 2009; Hallberg et al., 2018), criminal justice (Britt et al., 1996; Ramirez and Crano, 2003; Humphreys et al., 2017), fiscal (Bonham et al., 1992; King-Meadows and Lowery, 1996; Campbell and Allen, 2001) and less frequently agricultural (Ryu et al., 2017) policy or legislative and regulatory interventions. Notably, there has been negligible published research adopting an *ITS* methodology where undertaking analysis of planning and development policy (Galster et al., 2004).

In essence, this methodology utilises standard statistical modelling techniques to comparatively assess data within a single time series that has been partitioned into two epochs (Kontopantelis et al., 2015), representative of the periods both *prior* and *subsequent* to a defined implementation point related to the subject intervention (McDowall et al., 2019). The most prevalent statistical model applies *segmented regression* (Jandoc et al., 2015), in which the level (Cruz et al., 2017) and trend (referred to as slope) for the two periods are separately quantified, utilising appropriate regression techniques (such as *ordinary least squares*, *Poisson*, *logistic* (Bernal et al., 2017) and *non-linear* (Penfold and Zhang, 2013)), ultimately determined by the intrinsic characteristics of the data (Beard et al., 2019).

Commonly, a synthesised *counterfactual* scenario can be estimated, based upon the extrapolation of the pre-intervention model (Lopez Bernal et al., 2018), predicated upon the assumption that extant patterns would continue unaltered across the entire time period were it not for the intervention (Turner et al., 2019) [figure 2.7]

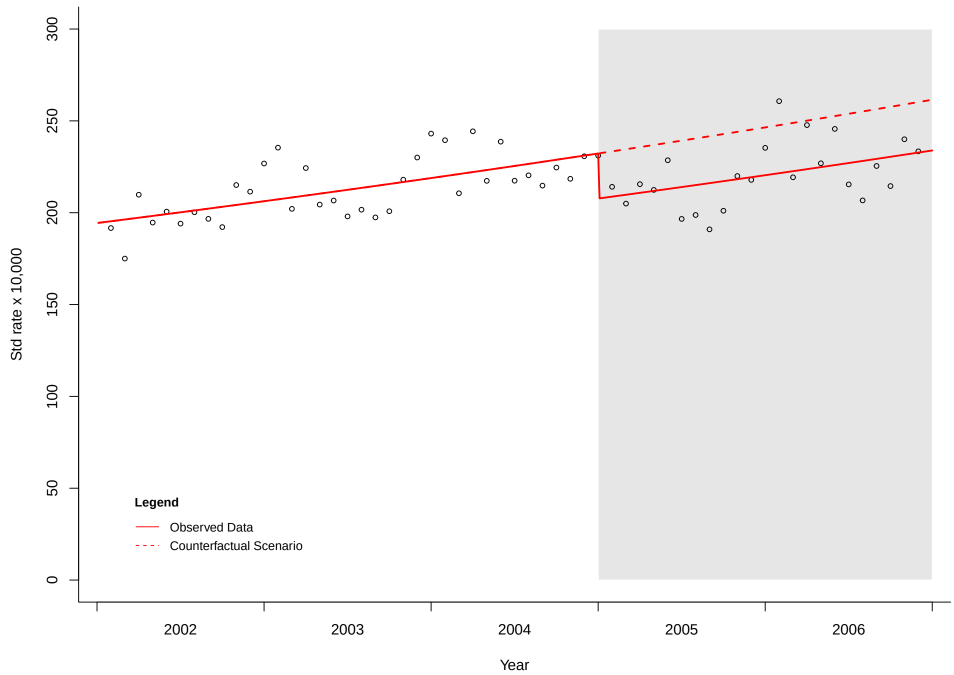

Figure 2.7: Source: *Bernal et al. (2017)*
The figure overlays modelled data relating to rates of *ACE* admissions between 2002 and 2006, relating to two respective segments based upon the time period prior to the enactment of a national public smoking ban and after, reflected by the white and grey backgrounds respectively. The continuous red line evidences the trends based upon the observed data, whilst the dashed red line synthesises the '*counterfactual*' scenario.

As a result *ITS* methods can account for the existence of secular trends in the pre-policy period (Penfold and Zhang, 2013), which could otherwise comprise the validity of the intervention effect.

Fundamentally, where the models produced in regards to the two comparative segments reflect a statistically significant difference, the effect of the intervention can be inferred (Linden and Yarnold, 2016). In the example of analysis based upon segmented regression the effect of the intervention can be expressed as either the difference between the slopes and levels of the two distinct periods (Wagner et al., 2002; Kontopantelis et al., 2015) or as an absolute difference between the estimated values derived from the post-intervention regression and the *counterfactual* scenario at a specific point in time (T_t) (Wagner et al., 2002).

2.7.3 Impact Evaluation Within the Context of Planning Policy

The incorporation of evaluative procedure into the planning system is well established (Guyadeen and Seasons, 2018). However, it has been dominated by *ex-ante* evaluation and in instances where *ex post facto* analysis has been conducted it has predominantly been focused upon outputs (such as plans and policies) rather than outcomes (Shahab et al., 2019).

Throughout relevant literature planning policy is recognised as consisting of two distinct approaches (Berke et al., 2006; Feitelson et al., 2017; Laurian et al., 2010; Oliveira and Pinho, 2010; Shahab et al., 2019). From the prevailing positivist epistemological perspective, the limited *ex post* impact evaluation undertaken regularly assumes a conformance based approach (Laurian et al., 2010), focused upon the extent to which patterns of development adhere to the original intention of the plan (Bulti and Sori, 2017).

For example Berke et al. (2006) investigated the degree of conformance to nine categories of developmental design intended to reduce potential storm related hydrological events. Based upon a combination of quantitative (derived from codes applied to planning permits) and qualitative data (based upon surveys), a conformance metric was derived, which reflected the percentage of relevant design techniques applied to each development. Whilst offering insight in regards to the relative success of the policy in achieving its intended aim of altering design approaches it could be accused of failing to measure the implicit outcome of reduced rates of surface run-off (Shahab et al., 2019) and gave little account for either unintended consequences (Oliver et al., 2020) or comparative analysis of the extent to which the policy had altered existing practice.

The alternative approach adheres to a performance based method, in which the evaluative procedure considers the impact of the plan upon decision-making process (Berke et al., 2006). Due to the nature of the process it is contended that there is limited scope for empirical analysis (Shahab et al., 2019), with qualitative assessment providing evidence around the perceptions of impacts rather than robust data relating to measurable outcomes (Baker et al., 2006).

With a narrow focus upon the success of a policy in regards to the delivery of intended outcomes (Shahab et al., 2019), allied to limited access to relevant data and the complexity of both the developmental stage (Laurian et al., 2010) and tangible outcomes (Hersperger et al., 2018), analytical research has been restricted (Hersperger et al., 2018; Shahab et al., 2019). Where quantitative analyses have been undertaken there has been a tendency to focus upon the associations between planning approaches and the patterns of development (Hersperger et al., 2018). To date there has been negligible research dedicated to the understanding of planning policy as an intervention (Dallimer et al., 2011), which could induce a change in the patterns of land use and land cover.

2.8 Planning in the United Kingdom

The planning system operated within the United Kingdom is considered relatively unique (Tewdwr-Jones, 1999), in so far as it has historically been characterised as broadly discretionary (Booth, 1995). Since the inception of formal planning procedures through the *Town and Country Planning Act 1947* (Cullingworth and Nadin, 2003), the approach has required Local Authorities to produce plans, which are intended to guide development at local level (Grant, 1992). Therefore, the majority decisions made in regards to development are made within the lowest tier of local governmental structures (DCLG, 2015b).

Within such a discretionary system decisions in regards to each application to develop are made on a case by case basis (Grant, 1992). Whilst decisions should generally abide by the agenda outlined within the local plan (Cullingworth and Nadin, 2003), there exists power to account for material considerations in the making of individual decisions (DCLG, 2015b). Although Allmendinger (2006) suggested the plan-led system had increasingly become analogous with a discretionary zoning system, planning within England has not shifted to a formal regulatory zoning approach, in which specific land parcels are allocated for particular land uses and where compliant development will be approved automatically (Gurran and Whitehead, 2011).

Local plans must be informed by and compliant with relevant National policy (Oxley et al., 2009). Consequently, National level planning policy can be understood to advance a development agenda (Oxley et al., 2009) and wields significant influence over changes to land use and land cover (Tewdwr-Jones, 1997).

Although access to green space has to some extent implicitly informed the planning system since it's foundation (Cullingworth and Nadin, 2003), there have been limited explicit policy or legislative provisions to protect such (Rydin, 1998). Where Howard (1946) developed the concept of '*garden cities*', in which planned urban settlements would both contain '*green spaces*' (Ward, 2005) and be encircled by functional, protected natural and semi-natural spaces (Buder, 1990), formal planning within the United Kingdom has not traditionally included provisions beyond the establishment of National 'Green Belts' (Cullingworth and Nadin, 2003). Potentially due to initial criticisms related to economic constraint and the aesthetic desecration of rural environments (Edwards, 1913), the '*garden cities*' approach did not evolve to inform early policy.

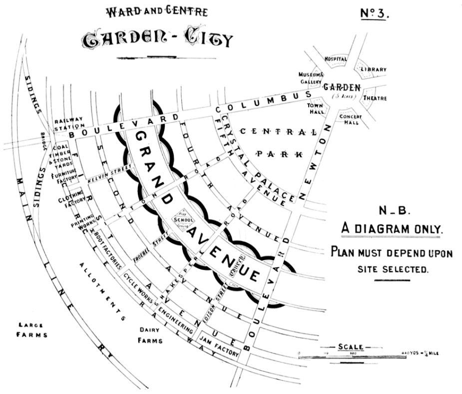

Figure 2.8: Source: Howard (1946) Diagram of proposed concentric lay-out of the garden city.

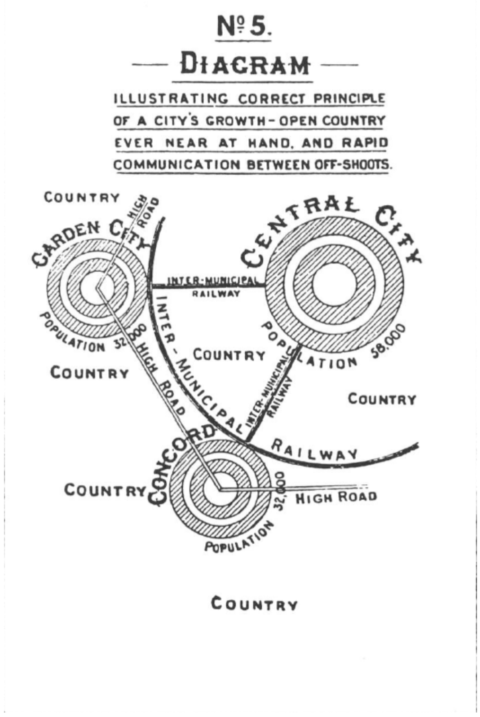

Figure 2.9: Source: Miller (1983) Illustrative diagram outlining the conceptual structure of the spatial relationship between the garden and central city.

Whilst the formal adoption of the '*garden cities*' approach did not occur, its influence was evident in the adoption of the principles of National 'Green Belts', which have persisted within the UK since 1955 (Cullingworth and Nadin, 2003).

Despite recognition of the importance of access to green space in regards to physical and mental health, no relevant conditions are incorporated into planning policy.

2.8.1 The Localism Act 2011 and The National Planning Policy Framework

The legislative basis for the revised planning framework was largely similar to its predecessor, with the *Town and Country Planning Act 1990*, *Planning and Compulsory Purchase Act 2004* and *Planning Act 2008* remaining in force (Winter et al., 2016). However, such were supplemented and amended by the *Localism Act 2011*, which established the *National Planning Policy*

Framework as the foundation for local plans (The Planning Inspectorate, 2019).

Whilst the revised framework remained contingent upon and constrained by the system of local plans (Slade, 2018), key provisions were considered likely to lead to a more permissive systems (Sibley-Esposito, 2014).

At a structural level the most significant change related to the abolition of *Regional Spatial Strategies* (Boddy and Hickman, 2013), which were intended to inform a strategic approach to growth (CLG, 2011), with protection of the environment recognised as a material consideration (ODPM, 2004). In conjunction with other key provisions, the revised framework could be interpreted as resulting in an increased degree of threat to '*green space*' and more specifically may contribute to a policy more encouraging of the expansion of urban areas beyond existing boundaries (Sibley-Esposito, 2014).

The most relevant elements of which are considered below, including; a) *the adoption of a presumption in favour of sustainable development*; b) *the use of previously developed land*; and c) *the protection afforded to 'Green Belt'*.

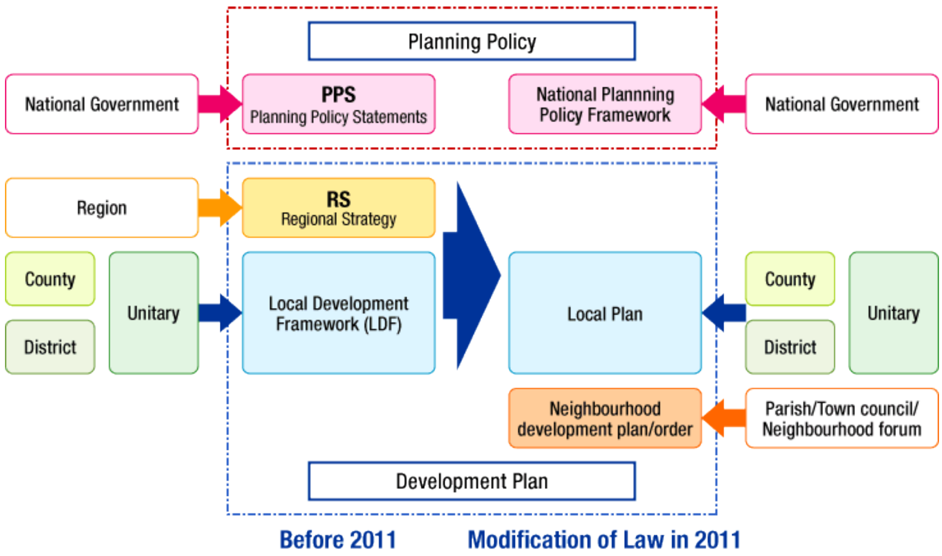

Figure 2.10: Source: Ministry of Land, Infrastructure, Transport and Tourism, Japan (2020)
UK National and Local Government Planning Structures both prior to and after the implementation of the *National Planning Policy Framework*.

2.8.1.1 Presumption in Favour

The *NPPF* introduced an underlying '*presumption in favour of sustainable development*', to which local plans would be required to adhere in order to be assessed as valid (Lees and Shepherd, 2015).

> *At the heart of the National Planning Policy Framework is a* ***presumption in favour of sustainable development****, which should be seen as a golden thread running through both plan-making and decision-taking.* (National Planning Policy Framework [s.14])

Under the provisions of the policy "*sustainable development*" is loosely defined around three dimensions of economic, social and environmental responsibilities (DCLG, 2012a). Considered in conjunction with a requirement for Local Authorities to "*positively seek opportunities to meet the development needs of the area*" (National Planning Policy Framework [s.14]) the lack of clear prescription (Nathan and Overman, 2011) saw the term conflated with both economic growth (Hannis and Sullivan, 2012) and residential development (Bell, 2018). With the most substantial weight afforded to developmental needs (Harris, 2012) unless, "*any adverse impacts of doing so would significantly and demonstrably outweigh the benefits*" (National Planning Policy Framework [s.14]) or land is subject to policies that "*indicate development should be restricted*" (National Planning Policy Framework [s.14]) (such as 'Green Belt' designation) the provision may be considered more akin to a general 'presumption in favour of development' (Bell, 2018).

It could reasonably be anticipated therefore that local plans must necessarily allocate larger areas of undeveloped land to meet development needs in order to avoid appeals (Harris, 2012) and the grounds upon which to refuse development would require a demonstrable negative impact. Subsequently, where green space is not subject to any additional protections the restriction of development would be unlikely. This can be considered a particular issue in relation to informal amenity spaces or pastoral agriculture, where there may be limited biodiversity or social value (Swanwick et al., 2003), but potentially core *regulating services* (Bolund and Hunhammar, 1999).

Crucially, in circumstances where a local plan was "*absent, silent or relevant policies* [were] *out-of-date*" (National Planning Policy Framework (2012) [s.14]) a Local Authority should not refuse development. Partially due to the abolition of *Regional Spatial Strategies*, which had formerly informed local plans (Hanusch and Glasson, 2008), and a revised method through which to assess housing need (MHCLG, 2015), the majority of Local Authorities were practically incapable of completing a review of local plans within the transitional period of 12 months (Lichfields, 2019). This was largely corroborated by research which evidenced that over a quarter of all Local Authorities remained without an approved plan by 2019 (Lichfields, 2019).

As a result, a greater number of speculative applications to develop upon 'greenfield' sites may have been submitted in the early period following the implementation of the revised framework based upon the assumption that they would have to be assessed against policies formed prior to the *NPPF* coming into force. Accordingly, where rejected such applications would be considered against an 'out-of-date' plan afforded little weight in law under appeal if it failed to evidence sufficient land to meet a five-year housing supply (Harris, 2012). Therefore, making it likely such proposals would be approved, particularly if shown to be providing residential accommodation.

CPRE (2018) reported rates of speculative application to build upon '*Green Belt*' were higher in 2018 than at any point since 2009. However, consideration must be given to the organisation's partiality (Slade, 2018) and the retention of protections within the framework, which were not overridden in the absence of a local plan (Bleasdale, 2013). Conversely, Sibley-Esposito (2014) presented evidence through which to suggest the lack of clarity within the reduced framework had led to unintended interpretations of the policy in regards to 'Green Belt', which may account for increased speculative applications.

	Development Plan Adopted and Up to Date	Development Plan either non adopted , not up to date, Silent or Indeterminate
Scheme accords with Development Plan	Approve without delay	Grant Permission
Scheme contrary to Development Plan	NPPF is silent	Grant Permission

Figure 2.11: Source: Harris (2012)
Conceptual framework of outcomes of an application to develop as outlined in the *NPPF*

In consequence a supposition can be posited that additional areas of green space would be subject to developmental pressure both due to inclusion within local plans and as a result of appeal.

2.8.1.2 Encourage the Redevelopment of 'Brownfield' Sites

Allied to provisions which may be associated with increased levels of development (Bell, 2018), the restrictions to the type of land upon which such should occur have been diminished (Sibley-Esposito, 2014). Under the policy framework established by the New Labour government the developmental onus had been upon the redevelopment of existing built sites, with explicit targets for the majority of new housing to be located on such (CLG, 2006).

However, where said prior policy established the reuse of previously developed land as an explicit "*priority*" (Planning Policy Statement 3 [s.36]), under the terms of the *NPPF* it was only encouraged.

> *Planning policies and decisions should encourage the effective use of land by re-using land that has previously been developed (brownfield land), provided that it is not of high environmental value.* (National Planning Policy Framework [s.111])

Whilst the *NPPF* replicated an intention to make "*effective use of land by re-using land that has previously been developed*" (Planning Policy Statement 3 [s.40]), it effectively removed the prior commitment towards a 'brownfield' first approach (Sibley-Esposito, 2014).

Ganser and Williams (2007) evidenced that the application of an explicit 60% target for 'brownfield' development had resulted in reduced 'greenfield' loss. It is therefore suggested as logical that the removal of the outlined target would potentially lead to an increase in development upon 'greenfield' land. It can be assumed that residential development on 'greenfield' sites may offer increased revenue for developers. Initial costs associated with development on 'brownfield' sites are higher than 'greenfield' equivalents, primarily as a result of preparatory commitments, including remedial ground works (Hutchison and Disberry, 2015). In addition to which, a relationship has been evidenced between the proximity of accessible green space and the price of housing (Morancho, 2003). Such access is more easily achievable where there already exists an abundance of green space, with significantly higher costs associated with the development of green areas upon land previously without vegetative cover.

The effect of this diminution in commitment to 'brownfield' development may have been evident by 2014. Despite sufficient land for the provision of 1.5 million homes on sites which had previously been subject to development (Sinnett et al., 2015), the number of applications to develop on 'greenfield' sites increased (Sinnett et al., 2014).

2.8.1.3 Green Belt Provisions

Based upon a simple interpretation of the provisions within the '*NPPF*' it could be reasoned 'Green Belt' land retained near identical protection to that which it was afforded under the previous regime [*PPG 2* (DCLG, 2006)]. However, such provisions were the subject of the most notable concern, primarily through the *Campaign to Protect Rural England* (Sibley-Esposito, 2014).

The *NPPF* transposed the five core purposes for the inclusion of land within a 'Green Belt' (National Planning Policy Framework [s.80]) and replicated relevant clauses from the prior framework through which to restrict designated land from inappropriate developmental threats.

> *As with previous Green Belt policy, inappropriate development is, by definition, harmful to the Green Belt and should not be approved except in very special circumstances.* (National Planning Policy Framework [s.87])

The types of "*very special circumstance*" in which development would be permitted also broadly conformed to the previous regime, with such being restricted to developments where the harm was demonstrably outweighed by other material considerations (DCLG, 2012a). Although the policy would additionally permit the development of prescribed facilities associated with, "*outdoor sport, outdoor recreation and for cemeteries*" and, "*the extension of a building provided that it does not result in disproportionate additions*" (DCLG, 2012a), neither were considered of significant risk to increased development (Bevan, 2017).

However, when considered in combination with other provisions within the policy and as a result of the removal of detail from the overall system (Upton, 2019), there were reasons to suggest the approach to development on 'Green Belt' had been interpreted as less restrictive than had been intended by government (Sibley-Esposito, 2014).

2.9 Research Literature Summary

The outlined research literature highlights the value and significance of green space as an environmental priority (Wolff et al., 2020), associating its preservation with planning policy (Herspeger et al., 2018). With evidence suggestive of the potential for the revised policy framework (under the provisions of the *Localism Act 2011* and *National Planning Policy Framework*) having altered the degree to which such land would be afforded protection from development (Sibley-Esposito, 2014). However, this proposition has not been statistically explored based upon data derived from a consistent methodology.

Considered as a driver or regulator of land change, analysis of the impact associated with national level planning policies is considered subject to common research priorities advocated by both Bürgi et al. (2005) and Plieninger et al. (2016), including the utilisation of non-remote sensed data, sample areas characterised by contextual stability and application of statistically more robust methods. In conjunction with prior UK based analyses relating to preceding policy, a research focus was developed to analyse the impact upon green space associable with the *Localism Act 2011* and *National Planning Policy Framework*, as an example of an isolable policy driver implemented within the context of a largely stable system (Morrison and Pearce, 2000), using practical impact evaluation tools (such as *Interrupted Time Series Analysis*).

CHAPTER 3

Methodology

Where Not Habitation Stood Before

3.1 Introduction

Cumulatively the elements of research undertaken in contribution to this thesis were designed to augment understanding of the influence of national planning policy as an underlying driver and regulator of land change due to urbanisation. It is contended the advancement of the field requires an improved understanding of the effects attributable to different policy systems (Alexander, 2016; Laurian et al., 2010; Shahab et al., 2019), adhering to a new conceptual framework through which to examine the myriad factors driving land use change (Plieninger et al., 2016).

Said framework recommends "*the deployment of more robust tools and methods to quantitatively assess the causalities of landscape change*" and advocates the use of a wider range of data sources than the reliance upon the predominant satellite imagery (Plieninger et al., 2016). However, such an approach is contingent upon the existence of a clear transition between two differing policy approaches within a single nation, supported by data relating to a discernible indicator of impact (Morrison and Pearce, 2000).

This research sought to address this gap by adopting a single land use change indicator, in the form of green space (upon which prior analysis had been undertaken and evidenced as effective (Dallimer et al., 2011; Mu et al., 2016)), in relation to the transition to the *Localism Act 2011* and *National Planning Policy Framework* in England. As an apposite subject of research, this policy change had been contended to have increased developmental threat to previously undeveloped land (Sibley-Esposito, 2014) and operated within a system previously hypothesised as responsive to policy change (Dallimer et al., 2011).

As the existence of a causal relationship was intended to be assessed, a quantitative approach was evolved (Morrison and Pearce, 2000). It was first intended to examine whether data could offer initial insight as to the existence of a structural change within rates of development upon green space, for which *change point detection* was employed. Prior to the use of *Interrupted Time Series* analysis as a means of discerning the effect associated with the policy change (Ramachandra, 2019). In the final stage of research the same *ITS* method was employed to investigate the extent to which the policy had potentially relocated development from existing urban boundaries to the rural fringe.

The outlined approach can be considered as an adaptation of the principal components described in Ramachandra (2019) for analysis of deforestation. *Change point detection* represents an established method through which to identify the occurrence of events through data analysis (van den Burg and Williams, 2020). Whilst the use of *Interrupted Time Series* analysis is expanding as a measure of intervention effects (McDowall et al., 2019).

3.2 Developing a Robust Land Change Data Set

In order to address the need for quantitative analysis of planning policy impacts (Plieninger et al., 2016) using the example of the *Localism Act 2011* and *NPPF*, data relating to the rate of development upon green space were required which continuously covered the period from before implementation to after. Whilst governmental records describing the extent of land undergoing transition from 'non-developed' to 'developed' forms were available for calendar years [January to December] between 1989 and 2011 (except 1999)(MHCLG, 2012) and financial years [April to March] between 2013 to 2014 and 2017 to 2018 (MHCLG, 2019a), methodological changes restricted the extent to which they can be reliably considered consistent and comparable.

Furthermore, relevant governmental data was not available in spatial format, therefore restricting analysis to the temporal. Although not the primary focus of the research it was essential to create a dataset that could be utilised both temporally and spatially, particularly to provide the means with which to investigate the extent to which different effects were evident within and outside of existing urban boundaries.

Thus, the initial stage of research aimed to produce a methodologically consistent, spatio-temporal green space loss dataset, upon which subsequent analyses can be conducted.

3.3 Sampling Methodology

Where practicable, analyses should be undertaken at a spatial scale consistent with that of the subject driver (Verde et al., 2020). Therefore, the impacts associable with the national level policy within this research would reflect outcomes derived from the whole of England. However, due to largely prohibitive data storage requirements, analysis was undertaken in regards to an aggregated sample (consistent with prior reseaarch (Dallimer et al., 2011)). 42 individual case studies were identified, based upon Local Authority Areas, at which level the planning process is generally administered (DCLG, 2015b) and funding pressures would be most keenly felt (Mell, 2016). It should be noted that said samples were not analysed individually as outcomes were considered likely to reflect local drivers rather than national policy effects. The aggregation of said samples were considered to represent a national spatial scale (Lloyd, 2016). Therefore, results must be understood to be associated with the identified spatial scale and are subject to potential spatial bias in accordance with the minimum areal unit problem (Openshaw and Rao, 1995).

Across the majority of England local government is structured as a two-tier system in which responsibility for relevant services are apportioned between the County [upper level] and District Councils [lower level]. However, a number operate within a single-tier, in which all services are unified (Local Governemnt Group, 2010). As of 2018 there were a total of 343 local authorities in England, incorporating 26 County Councils with a concomitant 192 District Councils, alongside 125 operating under a single tier of governance, which included 55 Unitary Authorities, 36 Metropolitan District Councils and 32 London Boroughs (Sandford, 2018).

In most instances responsibility for the majority of core planning functions resides within the outlined structure, under the jurisdiction of relevant single-tier authorities or District Councils, where a two-tier system exists (Sandford, 2018). There are exceptions in regards to significant infrastructural projects (such as in regards to transport, mineral extraction and waste) where County Council's act as the Local Planning Authority (DCLG, 2015b). In addition to which, central powers through the Greater London Authority allow for strategic oversight and enable it to make decisions in regards to some planing applications.

However, for the purpose of the research a decision was made to select samples from the core structure of District and single-tier Authorities. Therefore, the derived sample of 42 can be understood to reflect around 14% of the total eligible.

Sample LAAs were restricted to England only, due to both the limited availability of consistent authority profile data and existence of differing legislative or policy frameworks in regards to both Scotland and Wales prior to the start of the research period (Winter et al., 2016), thus limiting comparability.

3.3.1 Urban and Rural Designations

Local Authority Areas are classified as either 'urban' or 'rural', based upon the proportion of the population resident within permanent settlements with a recorded population of 10,000 or more (Bibby and Brindley, 2013). Where 74% or more of the total population reside within such areas an Authority is categorised as predominantly 'urban'. With 'rural' Authorities representative of areas in which fewer than 74% live within defined built-up areas (Bibby and Brindley, 2013).

At its most basic there are 6 distinct designations, which are advised to be used as the basis of statistical analyses due to the differing profiles of authority areas (DEFRA, 2011).

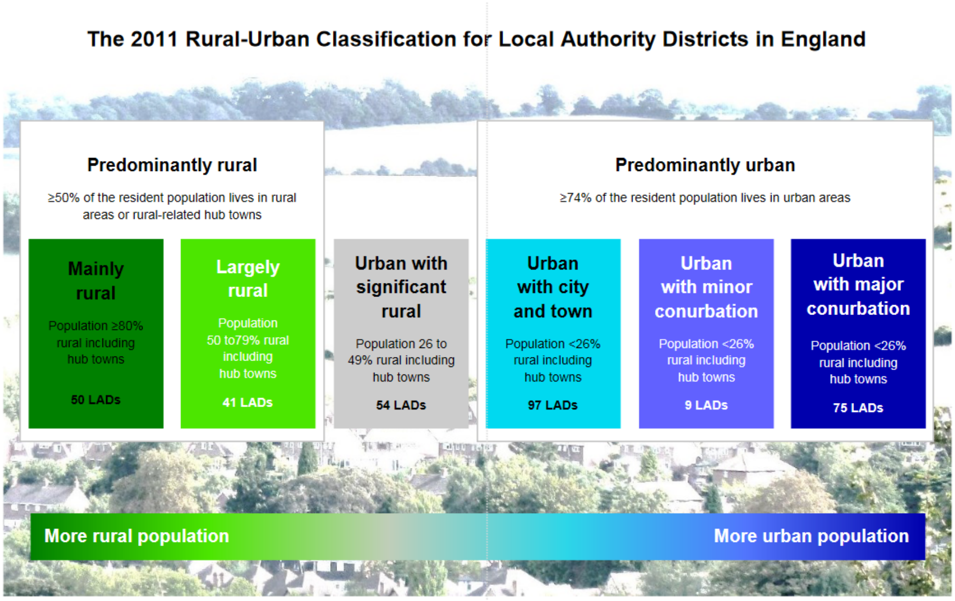

Figure 3.1: Source: DEFRA (2017)
Rural-Urban classification structures relating to Local Authority Districts in England from the 2011 census.

It must be understood however, the majority of a Local Authority Area may consist of open land cover, but be deemed 'urban' if 74% or more of the population reside within its urban settlements (Bibby and Brindley, 2013).

3.3.2 Sample Data

Certain key physical, economic and social characteristics pertaining to Local Authority Areas were recognised as materially influencing the extent to which developmental pressure may be applied (Briassoulis, 2009) and were consequently considered relevant to sample selection. Criteria included "*population pressure*" (Soemarwoto, 1985), total land area, the area of land subject to conservation protection, the area of land identified as being subject to the greatest risk of flooding (The Government Office for Science, 2010) and the promotion of economic growth (Travers, 2012).

In order to account for the potential influence of the outlined variables, relevant data was obtained to inform sample selection.

- **UK Census Data 2011:**
  Including *Rural-Urban Code*, *Rural-Urban Descriptor*, *Rural Population*, *Total Population*, *Total Area (Ha)* and *Population Density*.

- **Household Projections for England:**
  The "population pressure" (Soemarwoto, 1985) upon each Local Authority Area could be considered to constitute the recorded housing need. With no standardised mechanism through which to derive estimated data prior to 2016, household projections were utilised as an alternative, replicating a method described by Bramley et al. (2010). The annual change in population projections between 2006 and 2017 was calculated, with the average subsequently used as a proxy for "population pressure".

- **Housing Need Consultation Data (2017):**
  In the adoption of a new standardised approach to the assessment of housing need, data included a record of the *proportion of Local Authority land area covered by Green Belt, National Parks, Areas of Outstanding Natural Beauty or Sites of Special Scientific Interest*.

- **Flood Map for Planning (Rivers and Seas) – Flood Zone 3 (2016):**
  Data through which to identify areas at risk of flooding was accessed in polygonal form, through the governmental open data repository and represents land within *Flood Zone 3*. Land within *Flood Zone 3* is assessed as having a 1% or higher annual risk of experiencing fluvial flooding or 0.5% or greater of coastal flooding. Its use is well established in research fields (Faulkner and Wass, 2005; Gil and Steinbach, 2008; Percival et al., 2019) and acts as the primary basis for risk assessment within planning (Jones, 2008).

  The proportion of LAA area to constitute land at risk of flooding therefore was based upon the intersection between the *Flood Zone 3* data and the Authority Boundary.

- **Indices of Multiple Deprivation (2010):**
  Indices of multiple deprivation have previously been recognised as an indicator of the broad economic circumstances associated with different administrative levels within the UK (Abel et al., 2016). Data represents a relative assessment of deprivation based upon 38 weighted indicators, categorised under seven domains (income deprivation, employment deprivation, health deprivation and disability, crime, barriers to housing services and living environment deprivation) (Communities and Local

Government, 2007). As data was originally obtained at *Lower Super Output Area* [*LSOA*] level, which forms the lowest geographic layer within a Local Authority Area, the utilised deprivation score reflects the average of all LSOAs contained within the relevant LAA (Communities and Local Government, 2007).

Concentrations of deprivation were evidenced to be heavily associated with urbanity and geography (Communities and Local Government, 2007). 97% of the LAAs with the highest levels of deprivation were 'urban' and a larger number were situated in the North East and North West regions (Communities and Local Government, 2007).

The outlined data sets were subsequently joined to form a single matrix based upon common *Local Authority Area Codes* and *Names* (outlined in figure 3.2). This combined matrix was then split into 'urban' and 'rural' subsets. Due to the wide range of values associated with the different sample variables all were standardised to reflect a *z-score* [equation 3.1] (Jajuga and Walesiak, 2000).

$$z = \frac{x - \mu}{\sigma} \tag{3.1}$$

z represents the standardised value, x the original value, μ the population mean and σ the standard deviation of the population.

A framework representing relevant data structures is presented in **figure 3.2**

3.3.3 Sample Selection Considerations

In light of the potential for both individual characteristics and spatial correlation to influence the way in which planning policy may have been implemented (Briassoulis, 2009), sample Local Authority Areas were sought, which could be considered to represent the widest range. Thus, a simple randomly sampled approach to case study selection was rejected (Sharma, 2017). Whilst the adoption of non-random sampling techniques is commonly interpreted as weakening inferential analysis (Copas and Li, 1997), alternative methods may in some circumstances be more appropriate to the population (Schreier, 2018).

As an alternative, Chipeta et al. (2017) presented a spatially regular sampling design, through which to ensure spread within a population, thus reducing the

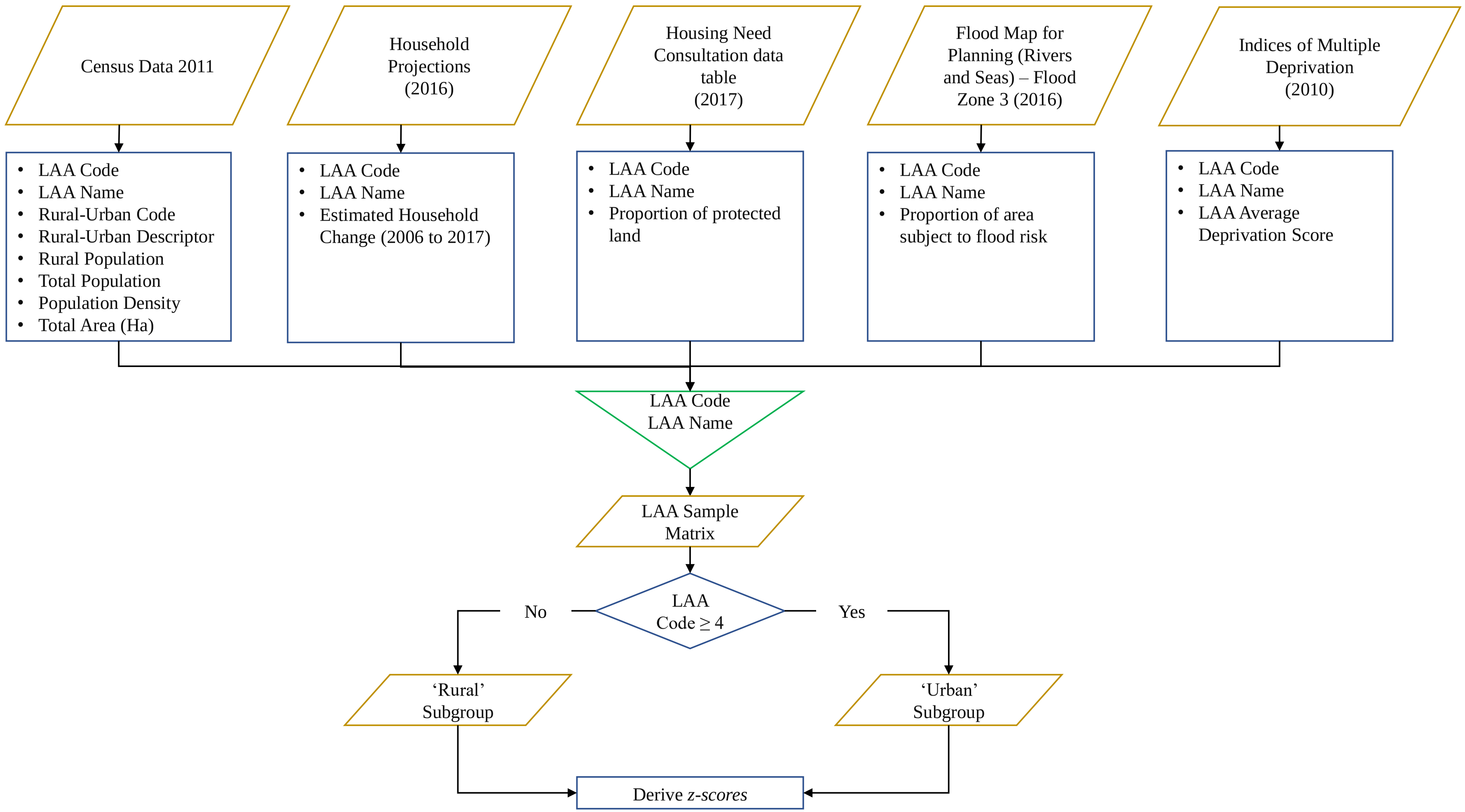

Figure 3.2: Sample data structure

risk of spatial correlation. Where this approach was deemed likely to yield a spatially representative sample, it would not explicitly account for other confounding factors. Therefore, an adapted *maximum variation* method was proposed.

In essence, *maximum variation* sampling is a purposive technique designed to ensure a sample reflects the widest range of the population (Cohen and Crabtree, 2006). It is conventionally utilised in qualitative survey based research (Marshall, 1996; Higginbottom, 2004), especially in circumstances where required to incorporate complex population dynamics (such as ethnicity) (Cohen and Crabtree, 2006). Although, not regularly applied to quantitative analyses, it was regarded as justifiable for this research as it would allow for the control of variables, which could be considered likely to otherwise confound inferential analysis (Cullingworth and Nadin, 2003). Whilst it also has established precedence in relation to intervention analysis (Fortin et al., 2019).

3.3.4 Sample Selection

The final sample was subsequently obtained through a method based upon *maximum variation* concepts and attempted to incorporate elements that could flexibly contribute to multiple analyses.

All data were processed using base functions in *R* (R Core Team, 2019). Within the 'urban' and 'rural' subgroups a single difference statistic was derived between each authority, reflecting the sum of the individual differences from the standardized core criteria (proportion of rural population, average change in projected population, proportion of land within LAA subject to legal protection, proportion of land area designated as being at the highest risk of flooding [*Flood Zone 3*] and deprivation score).

Based upon the outlined approach, samples were identified from each group as follows.

1. A primary sample Local Authority Area was identified at random.
2. A subsequent random sample was selected from the decile with least similarity based upon their cumulative difference statistics.

3. A final random sample was selected from the decile with most similarity based upon their cumulative difference statistics.

The summarised process was repeated until a total sample of 42 Local Authority Areas were obtained. Due to differences in area between each Local Authority a simple distance based proximity exclusion radius could not be used to ensure geographical dispersion. Therefore centroids were derived for each LAA. Where an Authority was selected as a primary sample the 10 nearest other LAAs were identified using a '*Nearest-Neighbour*' function (PostGIS, 2018) and excluded from subsequent selection as primary samples. As a result the derived sample Areas were geographically dispersed and reflected a wide range in regards to the sample variables [figure 3.3].

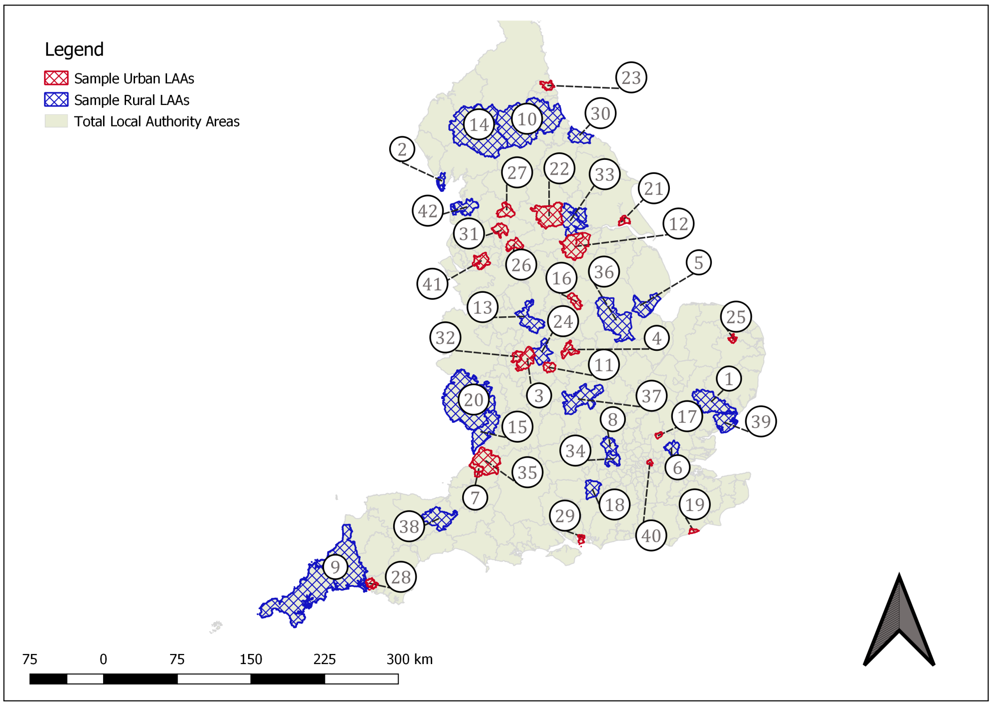

Figure 3.3: Source: Ordnance Survey (2018b)
Distribution of sample Local Authority Area, with 'rural' LAAs identified in blue and 'urban' identified in red.

1	Babergh	**15**	Forest of Dean	**29**	Portsmouth
2	Barrow-in-Furness	**16**	Gedling	**30**	Redcar and Cleveland
3	Birmingham	**17**	Harlow	**31**	Rossendale
4	Blaby	**18**	Hart	**32**	Sandwell
5	Boston	**19**	Hastings	**33**	Selby
6	Brentwood	**20**	Herefordshire, County of	**34**	South Bucks
7	Bristol, City of	**21**	Kingston upon Hull, City of	**35**	South Gloucestershire
8	Chiltern	**22**	Leeds	**36**	South Kesteven
9	Cornwall	**23**	North Tyneside	**37**	South Northamptonshire
10	County Durham	**24**	North Warwickshire	**38**	Taunton Deane
11	Coventry	**25**	Norwich	**39**	Tendring
12	Doncaster	**26**	Oldham	**40**	Tower Hamlets
13	East Staffordshire	**27**	Pendle	**41**	Warrington
14	Eden	**28**	Plymouth	**42**	Wyre

Table 3.1: List of the derived 42 sample Local Authority Areas.

3.3.5 Research Data

3.3.6 OS MasterMap® Topography Layer

Corresponding to the current governmental Land Use Change methodology (DCLG, 2015a), the primary data source in regards to the identification of both contemporary and historic green space was *Ordnance Survey Mastermap* (Ordnance Survey, 2017). This data is advanced as reliably and meticulously representing a comprehensive topography of the United Kingdom (Regnauld and Mackaness, 2006), including clear delineation of land use and land cover types (Barbosa et al., 2007). Deemed to offer a sufficiently high degree of spatial and temporal accuracy, the data has been utilised at both National (DCLG, 2015a) and Local scales (Liverpool City Council, 2010), in addition to which it has significant academic precedence in regards to green space identification (Barbosa et al., 2007; Tratalos et al., 2007; Davies et al., 2008; Moseley et al., 2013).

The digitally mapped data can be understood to be constructed from a nexus of polygonal, linear and point forms (Ordnance Survey, 2009), representative of relevant physical or social features (Regnauld and Mackaness, 2006), ranging from buildings to administrative boundaries (Orford and Radcliffe, 2007). The data comprises 5 separate elements, including *topographic area*, *topographic point*, *topographic line*, *cartographic text* and *cartographic symbol* (Ordnance Survey, 2017).

For the purpose of this research the primary source of data was the *topographic* *area* layer, in which physical features (such as buildings, roads, paths and land forms) are recorded (Orford and Radcliffe, 2007). Each feature is categorised under one of five '*Make*' designations based upon its form ('*manmade, multiple, natural, unclassified, unknown*'), which act as a primary classification criteria [figure 3.4]. Two additional sub-groups (*Descriptive Group* and *Descriptive Term*) offer further detail in regards to particular features (Ordnance Survey, 2017) [table 3.3.6].

Primary Classifier (*Make*)	**Secondary Classifier (*Descriptive Group*)**	**Tertiary Classifier (*Descriptive Term*)**
Manmade	Building	*N/A*
	General Surface	*N/A*
	Path	*N/A*
	Road or Track	Traffic Calming
	Structure	*N/A*
Multiple	General Surface	*N/A*
Natural	General Surface	*N/A*
	Natural Environment	Coniferous Trees; Coppice or Osiers; Heath; Marsh; Reeds or Saltmarsh; Non-coniferous Trees; Orchard; Rough Grassland; Scrub
	Rail	*N/A*
	Roadside	*N/A*
	Road Or Track	Track
Unclassified	Unclassified	*N/A*
Unknown	Unknown	*N/A*

Table 3.2: OS Data Structures representing primary ('*Make*'), secondary ('*Descriptive Group*') and tertiary ('*Descriptive Term*') classification criteria.

Figure 3.4: Data Source: Ordnance Survey (2018b)
Example of topographic layer data classified by '*Make*' and '*Descriptive Group*' (Ordnance Survey, 2017).

The features to be included as defined green space are predominantly portrayed within the data as individual polygons (Ordnance Survey, 2017) which can be identified through designation as 'natural' form (based upon primary classifier) (Barbosa et al., 2007; Tratalos et al., 2007; Mitchell et al., 2011). It should be noted however, that a single, large area green space, such as a park, accordingly consists of a collection of individual, unconnected polygons, restricting the capacity to identify an overall site [figure 3.5].

Figure 3.5: The figure shows an indicative sample of the representation of a 48.5 Ha public park in Coventry. Within the data said park consists of 102 separate 'natural' polygons and 52 classified as 'non-natural'.

The designation of any 'natural' land form as green space within this research was intended to include all elements of the urban typology identified by Swanwick et al. (2003) [figure 3.6], under the categories of *amenity*, *functional* and *linear* '*green spaces*', allied to *semi-natural habitat*. In addition to which, it would also incorporate all rural green spaces, in adherence to relevant land cover types outlined by Alcock et al. (2015).

MAIN TYPES OF GREEN SPACE			
ALL URBAN GREEN SPACE	Amenity Green Space	Recreation Green Space	Parks & Gardens
			Informal Recreation Areas
			Outdoor Sports Areas
			Play Areas
		Incidental Green Space	Housing Green Space
			Other Incidental Space
		Private Green Space	Domestic Gardens
	Functional Green Space	Productive Green Space	Remnant Farmland
			City Farms
			Allotments
		Burial Grounds	Cemeteries
			Churchyards
		Institutional Grounds	School Grounds
			Other Institutional Grounds
	Semi-natural Habitats	Wetland	Open/running water
			Marsh/Fen
		Woodland	Deciduous Woodland
			Coniferous Woodland
			Mixed Woodland
		Other Habitats	Moor/Heath
			Grassland
			Disturbed Ground
	Linear Green Space		River & Canal Banks
			Transport Corridors
			Other Linear Features

Figure 3.6: Source: Swanwick et al. (2003)
Categorisation of urban green space land types proposed by (Swanwick et al., 2003)

Whereas features indicative of developed form were founded upon the identification of any polygon where the primary classifier (*Make*) was recorded as '*manmade*', '*multiple*' or '*unclassified*' (Ordnance Survey, 2017).

Additional relevant fields within the data included; a unique ID [*TOID*], assigned to each polygon, which will remain throughout the life-cycle of the feature (Ordnance Survey, 2017); a *reason for change*, which acts as a record of the feature; and a *change date* which identifies the dates on which a polygon is created or undergoes significant amendment.

3.3.7 OS Address Base Premium

Allied to the *topographic area* layer outlined above, this research also incorporated *OS AddressBase Premium*® data, as a means by which to improve validity.

AddressBase Premium® represents any feature, which has an appropriate postal address and consists of around 40 million dated, geo-referenced spatial points (Ordnance Survey, 2016). It therefore provides a comprehensive record of every commercial and residential property within the UK and the dates at which said address was first recorded or was removed from the database (Ordnance Survey, 2018a).

In addition to the built environment, it includes certain classifications, which can be used to identify land and land use under broad categories of '*agriculture*, *burial grounds*, *forestry*, *allotments*, *amenity space*, *public open space* and *public parks*', previously utilised in relevant research (Mason et al., 2020).

3.3.8 Temporal Range

Having been stored in an accessible, archived data repository since 2007, *Mastermap*® data can be tracked over time, enabling direct comparison of land use change between 2007 and 2018 (Ordnance Survey, 2017). For each of the 42 sample Local Authorities, 12 digital maps were downloaded in *geodatabase* form (Zeiler, 1999), from the archive based upon available dates [table 3.3].

Research Time Period	**OS Archive Date**	**Time Between Data Sets (Months)**
2007	January 2007	N/A
2008	March 2008	14 Months
2009	March 2009	12 Months
2010	June 2010	15 Months
2011	June 2011	12 Months
2012	June 2012	12 Months
2013	December 2013	18 Months
2014	December 2014	12 Months
2015	January 2016	13 Months
2016	December 2016	11 Months
2017	November 2017	11 Months
2019	May 2019	18 Months

Table 3.3: Source: Ordnance Survey (2018b)
Dates associated with accessible archive of *Mastermap*® data.

Accordingly, the data relating to each time period reflects a record of the mapped data on the date at which it was archived (Sutton et al., 2007). Due to its large scale, all data was imported into and managed within Postgis, a geospatial, relational database system, which uses Structured Query Language [*SQL*] commands to manage and query spatial data (Corti et al., 2014).

3.3.9 Minimum Change Identification Method

For the purpose of this methodology the OS MasterMap® *topographic layer* data can be considered to consist of 12 distinct time points $(T_0, T_1, ...T_{11})$.

It should be noted that an accurate change data set could not be based solely upon the existence of a feature in time T, that did not exist in time T_{-1}. This was primarily attributable to both the update policy operated by *Ordnance Survey* (Ordnance Survey, 2020) and the method in which change was identified.

Under the terms of the published revision policy, *Ordnance Survey* categorise change into one of four distinct groups, each of which are subject to different time-frames in which to be recorded within the data (Ordnance Survey, 2020). Both *Prestige Sites* and *Category A* changes are recorded under a continuous process, within a maximum of 6 months of their occurrence. Whereas *Category B* and *C* changes are only subject to cyclical update, ranging from between a minimum of two and maximum of ten years, unless directly associated with a *Prestige Site* or *Category A* change and identified during the continuous update process (Ordnance Survey, 2020).

Therefore in regards to this research, relevant changes were restricted to those associated with either *Prestige Site* or *Category A* developments.

Examples of such consist of;

- *nationally significant infrastructure projects* (such as transport networks and associated termini);
- *Sites dedicated to the provision of core public services* (such as hospitals and educational establishments);
- *Regional and National sports stadia*;
- *Retail and Industrial developments*;
- *New residential dwellings (including large residential development sites)*;

- *New built development (except residential, agricultural or forestry) sites of any type*;
- *A new building within an existing site or an extension to an existing building that exceeds 0.10 Ha in area*;
- *The expansion or reduction of an existing [built environment] site that involves a change of topographic area where the total area changed is greater than 0.25 Hectares*;
- *A new built agricultural site greater than 0.25 Hectares*.

Throughout the development of the 'minimum change' method a range of approaches were developed and tested manually against both available aerial imagery and planning applications to ensure validity. Therefore, the final methodology summarised briefly below [outlined in full in Appendix **A**] represents the culmination of an iterative process.

Stage 1: All Recorded Change

The first step in change identification utilised the fact that the unique ID of any new topographical object recorded in the data at time T would not exist in the equivalent data for time T_{-1}. Such would not imply that the new polygon necessarily constituted a genuine change, but provided the basis for subsequent stages.

Stage 2: Identification of Prestige Buildings and New Residential Features

Based upon their prominence within the revision policy, both buildings associated with a *Prestige site* and all new residential developments were prioritised (Ordnance Survey, 2020). Relevant sites were identified where they contained a new building associated with one of 26 relevant *AddressBasePremium*® classification codes (which only existed in the data after time T_{-1}). Subsequently all new built infrastructure (categorised as '*manmade*' or '*multiple*') contained within the development site was incorporated as change data [figure 3.7].

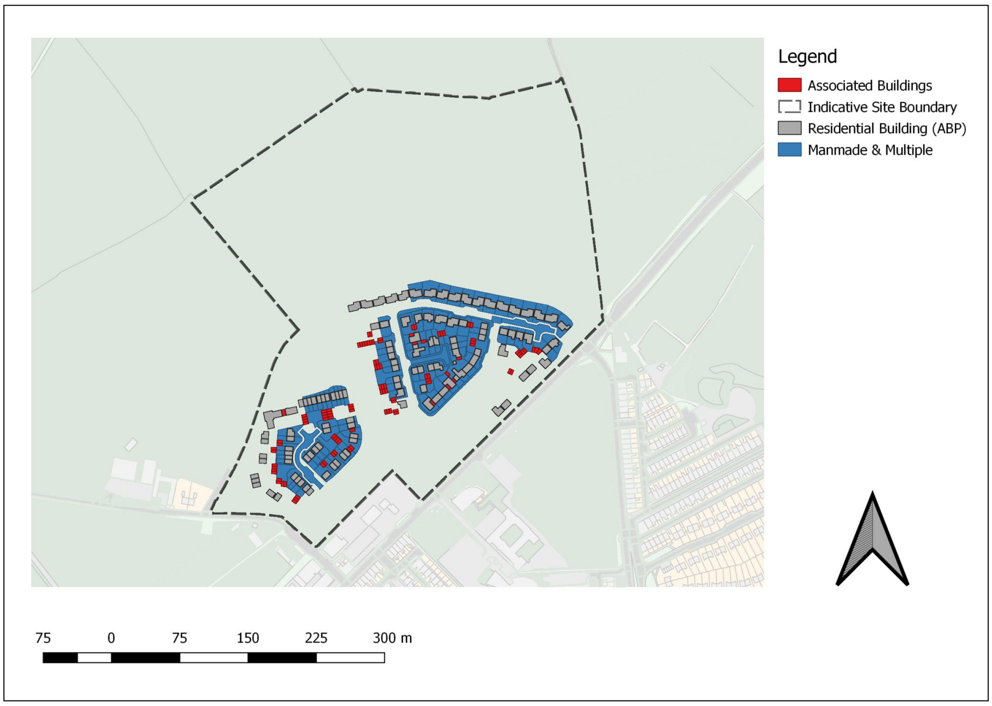

Figure 3.7: Data Source: Ordnance Survey (2018b)
Indicative change data. Land which has transitioned from 'green space' to new residential building is denoted by grey polygons. Land which has transitioned from 'green space' to any 'manmade' or 'multiple' form are shown in blue. Land which has transitioned from 'green space' to associated non-residential buildings are red. The dotted line reflects the indicative boundary of the site upon which development occurred.

Stage 3: Retail and Industrial Development

In regards to both retail and industrial development included within the terms of *Category A* change, a broadly similar approach to **stage 2** was applied.

Initially therefore, commercial retail or industrial sites were identified as any polygon which contained a new building (as identified in **stage 1**) where *AddressBase Premium*® recorded it as such. Thereafter, all other new '*manamde*' features within the site were joined as constituents of change data [figure 3.8].

Figure 3.8: Data Source: Ordnance Survey (2018b)
Indicative industrial change data. Land which has transitioned from 'green space' to new industrial building is denoted by grey polygons. Land which has transitioned from 'green space' to any 'manmade' form is shown in blue. Land which has transitioned from 'green space' to associated non-industrial building is red. The dotted line reflects the indicative boundary of the site upon which development occurred.

Stage 4: Agricultural Developments

Within the revision policy, both new and expanded built features associated with agricultural sites must be of 0.25 Ha or greater in order to be classified as *Category A* and thus identified within 6 months of occurrence. Due to the terms of the outlined condition it was possible to identify both new and extended features within a single stage.

Consequently, such sites were distinguished within the data using an adapted approach. Where previously the initial stage of identification was based upon relevant *AddressBase Premium*® data being contained within a new building, for agricultural sites it included association with any recorded '*manmade*' surface.

All new features categorised as '*manmade*' or '*multiple*' contained within the indicative agricultural site were merged to form a single polygon. The relative area for this site was calculated and if equal to or in excess of 2500m^2, its constituent elements were included within the relevant change data [figure 3.9].

Figure 3.9: Data Source: Ordnance Survey (2018b)
Indicative agricultural change data. Land which has transitioned from 'green space' to new industrial building is denoted by grey polygons. Land which has transitioned from 'green space' to any 'manmade' form is shown in blue. Land which has transitioned from 'green space' to associated non-industrial building is red.

Stage 5: Developmental Preparation

Although excluded from the government's land use change methodology (DCLG, 2015a), *OS* categorise land which is in the process of undergoing development using the '*unclassified*' designation (Ordnance Survey, 2017). Consequently, it is feasible to identify land at the earliest stages of development and include such as a form of change. This encompasses both the occurrence of development upon designated 'natural' and existing built forms [figures 3.10 and 3.11].

Figure 3.10: Data Source: Ordnance Survey (2018b)
Site in time T_{-1} consisting of both 'natural' and 'non-natural' features.

Figure 3.11: Data Source: Ordnance Survey (2018b)
Site at time T, in which it has undergone change to 'unclassified'.

As the ID of an '*unclassified*' polygon remained the same as the largest feature it had replaced, such data was not identified as an element of the 'provisional change' data set produced in **stage 1**. Therefore, the identification of land subject to development between time intervals can be understood to reflect the spatial intersection of two polygons, which were classified as one form at time T_{-1}, but had become '*unclassified*' in time T.

Whilst not explicitly outlined, it is assumed the primary reason for the omission of changes to '*unclassified*' form was based upon the fact that the development may subsequently restore elements consistent with the previous '*make*'. Thus not necessarily reflecting a genuine change of land use. However, with the research focus upon understanding the impact of development it was deemed imperative to include such.

Consequently, there is the potential to over-estimate the area of land lost permanently to development. However evidence suggests green space land directly associated with developments is often perceived as inaccessible (Wendel et al., 2012). Whilst additionally, it offers the only means by which to identify large scale developments, which may occur over many years, at a point more consistent with their approval. Furthermore, with an identical methodology applied to the entire data set the inclusion of such should not be deemed to compromise derived inferences.

Stage 6: Combined Change

Having created four distinct change data sets (**stages 2** to **5**), the individual elements were joined into a single multi-polygon file reflecting the minimum change which had occurred in time T. The area to have undergone transition from green space to indicative developed form, therefore represented the spatial intersection between any area identified as 'natural' in time T_{-1} and the derived change dataset [figure 3.12].

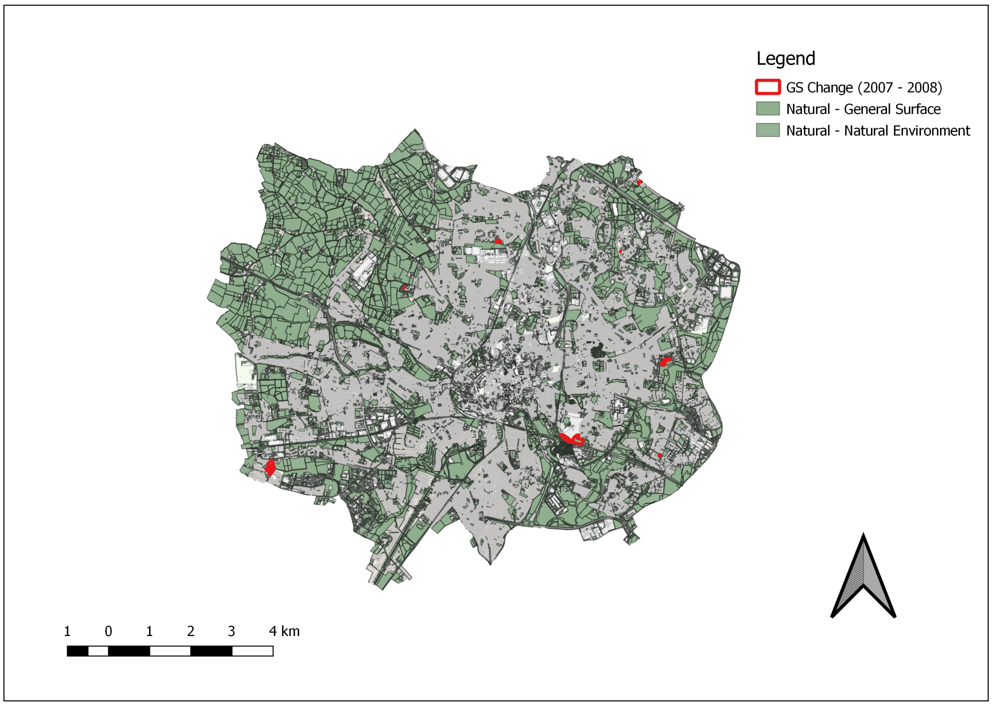

Figure 3.12: Source: Ordnance Survey (2018b) An example of the total identified area of change from 'natural' to indicative developed form in a single LAA [Coventry] between 2007 and 2008.

Stage 7: Removal of Indicative 'Brownfield' Change

Where based solely upon the designation of land as 'natural', sites were included which would be categorised as 'brownfield' for the purpose of planning policy. Therefore, in any circumstance in which the 'natural' space (in time T_{-1}) upon which development occurred contained an *AddressBase Premium*® classification code denoting the existence of built infrastructure at any point prior to time T_{-1} it was removed from the 'green space loss' data and stored as a separate dataset.

Each geospatial polygon of the derived green space loss data set comprised pre-change and post-change unique IDs; geometric attributes (such as area (m^2), shape and location); both pre-change and post-change classification criteria (‘*Make*’, ‘*Descriptive Group*’ and ‘*Descriptive Term*’); and a time of change identifier (consisting of quarter and year).

3.4 Primary Green Space Loss Datasets

Throughout the research a number of distinct green space datasets were utilised. **Chapters 4** and **5** are based upon analysis of cumulative green space loss derived through the ‘minimum change methodology’ [3.3.9] and a ‘*construction normalised*’ equivalent. Whereas **chapter 6** focuses upon green space loss which occurred within designated ‘Green Belt’; green space loss in relation to indicative urban boundaries; and ‘brownfield’ loss contained within urban boundaries.

The primary datasets (utilised in chapters 4 and 5) are detailed in the following section, but those used in regards to **chapter 6** are described in the relevant section [6.3.3].

3.4.1 Primary Green Space Loss Data

Using the time of change identifier, two distinct univariate time series were derived, consisting of 12 (inter-annual) ($t_0, t_{+1}, ..., t_{+11}$) and 48 (inter-quarter) ($t_0, t_{+1}, ..., t_{+47}$) observations respectively. Each represent the aggregate area of green space loss, which had occurred during each time interval, relating to the 42 sample authority areas. As such, it could be understood to reflect the sum of the area (m^2) of land which was recorded as as having changed from green space to an indicative ‘developed’ classification [as defined in section 3.3.9] between any two consecutive time intervals within the research period and is represented mathematically in **equation 3.2**.

For a time series Υ, consisting of $0, ..., m$ observations (where $m = 12$ for annual and $m = 48$ for quarterly data), the area of green space loss at times $t_0, ...t_n$ (where $n = +11$ for annual and $n = +47$ for quarterly data) is;

$$GSL_t = D_\Upsilon \cap GS_{\Upsilon-1} \qquad for \quad \Upsilon = 0, ..., m \tag{3.2}$$

the area of intersection ($\cap$) between land recorded as ‘developed’ in time Υ (D_Υ) and green space in time $\Upsilon - 1$ ($GS_{\Upsilon-1}$).

Figure 3.13: Data Source: Ordnance Survey (2018b)
An example of an individual polygon reflecting 'green space loss' data.

Local Authority	Year	Quarter	Time	Recorded Area Green Space (2007 - GS Loss)	GS Loss (m^2)
Coventry	2007	1	1	43159162.54	38340.18
Coventry	2007	2	2	43120822.36	0.00
Coventry	2007	3	3	43120822.36	10788.75
Coventry	2007	4	4	43110033.61	52098.35
Coventry	2008	1	5	43057935.26	4044.89
Coventry	2008	2	6	43053890.38	15214.89
Coventry	2008	3	7	43038675.49	167.37
Coventry	2008	4	8	43038508.12	249.85
Coventry	2009	1	9	43038258.27	237.75
Coventry	2009	2	10	43038020.52	43.08
Coventry	2009	3	11	43037977.43	77766.21
Coventry	2009	4	12	42960211.23	16590.64

Table 3.4: Example of generated green space loss data relating to Coventry (2007 - 2009).

In order to account for the availability of relevant land, the data was converted to reflect the area of green space (m^2) which underwent development as a proportion of the total available area of green space (Ha) at the time in which the change occurred, hereafter referred to as the '*green space loss ratio*' [equation 3.3].

For a time series t, consisting of $0, ..., n$ observations (where $n = +11$ for annual and $n = +47$ for quarterly data).

$$GSLR_t = GSL_t/(GLA_{t-1}/10000) \qquad for \quad t = 0, ..., n \tag{3.3}$$

$GSLR$ should be understood to reflect green space loss as a proportion of the total available area of green space (m^2/Ha), GSL the total area of green space identified as having undergone change to developed form (m^2) and GLA the total area of green space (m^2).

3.4.2 Confounding Variables

Where undertaking research based upon the identification of causal inference Morrison and Pearce (2000) recommends the need to address the potential influence of confounding variables. Through relevant literature a variety of economic, natural, cultural and technological factors were identified (Bürgi et al., 2005; Hersperger et al., 2018; Morrison and Pearce, 2000; Nuissl and Siedentop, 2020).

Due to the dual identification of change through both *OS MasterMap®* and *AddressBase Premium®* built environment (Ordnance Survey, 2017, 2018a) classification criteria the effect of natural drivers of land change was considered unlikely. Natural induced land change (such as landslides (Bürgi et al., 2005)) would neither be reflected as change under the *topographic layer* revision policy adopted for this research (Ordnance Survey, 2020) nor associated with a new *ABP* postcode record (both of which were required for change to be verified).

Similarly, the identification method was considered a reliable control for potential technological drivers of change, which generally relate to conversion between different agricultural uses (Corbelle-Rico et al., 2015).

Whilst research has recently evidenced a cultural shift towards a preference for less dense accommodation across much of Europe (Nuissl and Siedentop, 2020), there is little evidence of a similar effect in the United Kingdom, where housing preferences have remained similar (Orford and Radcliffe, 2007). Equally it is contended the regulatory functions of planning policy offer the means through which to limit the effects of this driver (Baing, 2010) and therefore should be considered unlikely to invalidate the inference of this research. Whilst the effects of neighbourhood interactions, such as the distance between residential and industrial land uses (Nuissl and Siedentop, 2020), were considered unlikely to have altered during the period.

The most significant inferential threat was associated with the effect of economic circumstance upon overall rates of development. The research period coincided with the global economic crisis of 2008 to 2009 (Tatliyer, 2017), which was identified as suppressing both construction (Edmund et al., 2009) and planning applications (Marrs, 2019). Where research in which the effects of the recession were similarly considered likely to affect the inferential outcome a standard approach has been to exclude the period prior to 2009 (Lane and Hall, 2019). However, in regards to this research within the context of the planning system, the potential for a lagged effect upon rates of construction was considered to require an alternative measure of control.

Therefore, to control for the potential for the data to merely reflect trends attributable to the economic climate rather than the effects of the policy intervention, authority level construction statistics were obtained, in the form of governmental records of the number of residential building projects started within each quarter (MHCLG, 2020c). Data was suitably lagged by 2 quarters to account for the time frame associated with the *Ordnance Survey* revision policy (Ordnance Survey, 2020).

Local Authority	Year	Quarter	Time	Total Building	Lagged Year	Lagged Quarter	Lagged Time
Coventry	2006	3	-1	350	2007	1	1
Coventry	2006	4	0	180	2007	2	2
Coventry	2007	1	1	310	2007	3	3
Coventry	2007	2	2	280	2007	4	4
Coventry	2007	3	3	330	2008	1	5
Coventry	2007	4	4	150	2008	2	6
Coventry	2008	1	5	60	2008	3	7
Coventry	2008	2	6	40	2008	4	8
Coventry	2008	3	7	100	2009	1	9
Coventry	2008	4	8	30	2009	2	10
Coventry	2009	1	9	90	2009	3	11
Coventry	2009	2	10	50	2009	4	12

Table 3.5: Example of construction statistics, reflecting the number of residential building construction sites begun in relevant quarters. The outlined example reflects data relating to Coventry for the period equating to 2007 to 2009.

An adjusted '*construction normalised green space loss*' variable was derived for the quartered data set, reflecting the '*green space loss ratio*' per 100,000 developments started [equation 3.4]. This data was also subsequently rescaled to the annual time series to enable comparable analysis. Consequently, where there was reduced total development, the area of green space undergoing transition to developed form would constitute a more significant figure than the same area at a time where rates of total development were higher.

For a time series t, consisting of $0, ..., n$ observations and a second time series θ, consisting of $-2, -1, 0, ..., n$ observations, the '*green space loss ratio*' per 100,000 developments started at times $\sigma_0, ...\sigma_n$ (where $n = +47$) is;

$$CWGS_\sigma = GSLR_t/(CON_{\theta-2}/100000) \qquad for \quad t = 0, ..., n \quad and \quad \theta = -2, ..., n \tag{3.4}$$

where $CWGS$ represents the construction normalised '*green space loss ratio*', $GSLR$ '*green space loss ratio*' and CON the total recorded development projects started.

For example, in regards to the years 2007 and 2008 '*green space loss ratio*' was recorded as 2.07m^2/Ha and 1.79m^2/Ha respectively. However, when normalised by total development, comparable data was recorded as 6.96m^2/Ha (per 100k development projects) in regards to 2007 and a higher figure of 9.86 m^2/Ha (per 100k development projects) in regards to 2008.

Said data was deemed to offer a suitable proxy, which accounted for both contemporaneous, direct economic impacts (Brauers et al., 2013) and consequential effects attributable to rates of applications for planning permission. In addition, the outlined data was available at a spatial scale consistent with the research samples, which was not the case with alternative control variables, such as weighted Gross Domestic Product data (Murphy, 2009), which could have been incorporated into relevant models.

However, it should be understood that as relevant data only account for residential developments it may underestimate the extent of change occurring at each interval. Despite this caveat, rates of residential development were highly reflective of the recession and recovery (Department for Business, Innovation and Skills, 2013), intimating they can be considered to offer a stable estimation of the economic profile (Lichfields, 2016) and represented the most viable data set through which to control (Olga and Antonios, 2019).

3.4.3 Change Point Detection

The methodological approach to *change point detection* undertaken in **chapter 4** is summarised below. For a more detailed description refer to section 4.2.6.

In regards to the research time series (for example $t_0, ..., t_{+47}$), change points reflect any quarter (τ) in which the statistical properties associated with $t_0, ..., t_\tau$ are structurally different from $t_{\tau+1}, ..., t_{+47}$.

The primary *Change Point Detection* method, assuming a single point of change, applies a *Maximum log likelihood ratio* technique (Killick and Eckley, 2014). The change point is identified as the point in time at which the difference between the test statistic (e.g mean, variance or both) relating to two segmented time periods is least similar to the same statistic derived from the entire period [equation 3.5] and exceeds a defined threshold (referred to as a penalty).

$$\hat{\tau} = argmax\{log(x_{1:\tau}) + log(x_{\tau+1:n}) - log(x_{1:n})\} > \lambda \tag{3.5}$$

Where $\hat{\tau}$ represents the time interval in the data estimated as the most likely change point, τ the time interval tested as the change point, x *green space loss ratio* data, n the final time interval and λ the penalty value.

As a means through which to enhance the strength of this research (Messer, 2019), the test statistic was defined as the mean and variance of the area of '*green space loss*'. It was not assumed that a single change point would occur within the data, therefore an adapted approach allowing for multiple structural changes was adopted (Haynes et al., 2017).

An identical process was followed in regards to each data set (cumulative and subset ('urban'/'rural') '*green space loss*' and '*construction normalised green space loss*'). Initially, a range of logical penalty values were tested using in-built *Pruned Extract Linear Time* [*PELT*] and *Change Points for a Range of PenaltieS* [*CROPS*] algorithms (Killick et al., 2012). Said algorithms calculated the negative log-likelihoods associated with each possible segmentation of the data. Subsequently, the derived *cpt* value was used to identify the optimal number of change points and relevant penalty value (Haynes et al., 2017), which was applied to the programme as a manual value.

3.4.4 Interrupted Time Series Analysis

To derive a quantifiable policy intervention effect, an *Interrupted Time Series* analysis approach was adopted. In light of the fact that the research was focussed upon the retrospective analysis of the effect of a policy, for which it was reliant upon secondary data and access to a viable control group was infeasible, the *ITS* method was considered to offer the most robust inferential scope (Wagner et al., 2002). In addition to which it has widely been utilised in policy research across a variety of sectors [section 2.7.2] and is advocated as addressing matters of complexity through the use of a mathematically synthesised counterfactual (HM Treasury, 2020b).

The criteria upon which research is deemed suitable for *ITS* analysis is based upon three core elements, encompassing the ability to accurately define *pre-* and *post-policy* periods, the identification of an interpretable outcome and the availability of suitable data (Bernal et al., 2017). Each of which can be met for this research.

Whilst there is no minimum observation number required for *ITS* analysis, with the uniform distribution of data around the intervention and the absence of confounding characteristics (such as *seasonality* and *autocorrelation*) highlighted as more significant (Bernal et al., 2017), there is evidence to suggest that a larger number of observations would improve the validity of regression based inferences (Zhang et al., 2011; Jandoc et al., 2015).

It was primarily for this reason all data was divided into 48 inter-quarter observations, with relevant pre-analytical tests undertaken in regards to *seasonality* and *autocorrelation*.

To support the derived inferences two distinct approaches to *ITS* analysis were adopted. The first replicated existing standard methods through the use of segmented regression with an adaptive *generalised least squares* regression (Lane and Hall, 2019). Whilst the second applied a forecast model technique (Linden, 2018), in which a *dynamic linear model* was utilised as an alternative to more common *ARIMA* or *Holt-Winters* models, in regards to which insufficient observations existed to enable implementation (Chen et al., 2008; Jandoc et al., 2015).

The *ITS* methods applied throughout this research can be considered to consist of three stages, the first of which establishes relevant *pre-policy*, *post-policy* and *transitional* periods. Subsequently, appropriate statistical models were fit to the data, with a synthesised 'counterfactual' extrapolated for the *post-policy* period based upon the supposition that prior trends would continue unaffected without the policy change. Finally, intervention effects were calculated using two different methods, reflecting both standard, existing approaches and an adapted alternative.

The segmentation of data was consistent in regards to the methods applied in both **chapters 5** and **6** and is discussed below. Whilst the principles underpinning further stages are summarised with detail provided in relevant sections.

Temporal Segmentation

As outlined, a core consideration in regards to the *ITS* approach related to the differentiation of accurate *pre-* and *post-policy* intervention periods (Bernal et al., 2017). Whilst the revised policy framework could be identified as having been introduced in two stages, between November 2011 (Localism Act, 2011) and March 2012 (MHCLG, 2012), a significantly lagged effect was anticipated (Crane and Weber, 2015). In circumstance in which such lagged effects are expected researchers have traditionally adopted one of two approaches, either modelling the transitional period separately (Wagner et al., 2002; Lane and Hall, 2019) or removing it from analysis (Penfold and Zhang, 2013; Hopewell et al., 2012).

Accordingly, the research must be understood within the context of the relevant administrative and physical time frames associated with the planning process, from application to the commencement of construction on site. Allied to which, additional consideration should be given to the potential impact of the data revision policy operated by *Ordnance Survey* (Ordnance Survey, 2020).

The maximum anticipated time delay between the implementation of the policy and evidence of effects that could be associated with it, is based upon the total time between application and the start of construction, with the addition of the maximum delay between such and it being recorded in the data by *Ordnance Survey* [equation 3.6].

Whereas, the minimum assumes that approvals made after the date of implementation were dependent upon the revised policy and accounts only for the time between the approval of an application and beginning of construction, allied to the same maximum data update time [equation 3.7].

$$max(lag) = \tau^{p1} + \tau^{p2} + max(\tau^{os} \tag{3.6}$$

$$min(lag) = \tau^{p2} + max(\tau^{os}) \tag{3.7}$$

Where τ^{p1} represents the time between the submission of a planning application and approval (by the *Local Planning Authority*), τ^{p2} the time between approval and the start of construction on site, and $max(\tau^{os})$ is the maximum time in which *Ordnance Survey* would record the development.

Time Frames

In its most simple form the time between the submission of a planning application and a decision being made should be between a minimum of eight and maximum of sixteen weeks, dependent upon circumstances (DCLG, 2015b). However, in regards to more complex cases and where the decision is subject to an appeal to the *Planning Inspectorate* this time frame can increase to a total of around twenty-two weeks (DCLG, 2015b). Governmental data suggests that between 58% of major and 81% of other developments were approved within relevant statutory time frames during the first year under the provisions of the *NPPF* [2012/2013](MHCLG, 2020b). Whilst, based upon a sample of 12 planning authorities [including 1 used within this research] Ball et al. (2009) reported a mean average of 8 weeks, with an associated maximum of 14 weeks. Therefore, it was deemed logical to assume a conservative 3 month time frame between application and approval.

Determined by the type, the maximum period after approval in which construction must begin was limited to five years prior to 2009 and three years thereafter (MHCLG, 2020d), with limited exceptions. Therefore, an absolute maximum delay between approval and construction for the period of interest to the *ITS* analysis was three years. In practice however, the time frame between approval and the commencement of ground works was evidenced as being substantially lower (Shelter, 2019). Based upon the 1.7 to 3.2 year time frame reported by the *Callcutt Review* (Callcutt et al., 2007), 2.6 year average identified by the *Local Government Association* and between 10 and 18 months, dependent upon site scale reported by Lichfields (2016), a 2019 study by Shelter (2019) applied a two-year estimate to the lag between planning approval and the completion of construction on a site. From the outlined estimates a time frame of 12 months was adopted for the purpose of subsequent sensitivity testing.

As outlined within the published revision policy, *Ordnance Survey* endeavour to ensure that the types of change incorporated into the '*green space loss*' dataset would be recorded within no more than six months of their occurrence (Ordnance Survey, 2020).

Based upon the above a maximum lag of 21 months was estimated, whilst the minimum was 18. Within the context of the temporal range of the data, these estimated lags were considered to equate to the years 2012 and 2013, which would therefore be recorded as a transitional phase and removed from the respective modelling. However, sensitivity testing was conducted during the modelling stage in order to assess the validity of this supposition.

Defined Analytical Segments

Initially, the *pre-policy* period was defined as the 20 observations between quarter 1 of 2007 and quarter 4 of 2011, with the respective *post-policy* period equating to the 20 observations relating to quarter 1 of 2014 to quarter 4 of 2018. This approach assumed that the transitional phase [between 2012 and 2013] would primarily continue to reflect the active policy framework prior to 2011, with any intervention effect not being evident until at least 2014 [figure 3.14].

Whilst not included within modelling of the *pre-policy* period, the transitional period is accounted for within analysis in order to maintain sufficient observations with which to ensure the validity of such (Lane and Hall, 2019). By adopting this approach to segmentation it also ensured an equal distribution of observations within both the *pre-* and *post-policy* periods, in adherence to recommended procedure (Bernal et al., 2017).

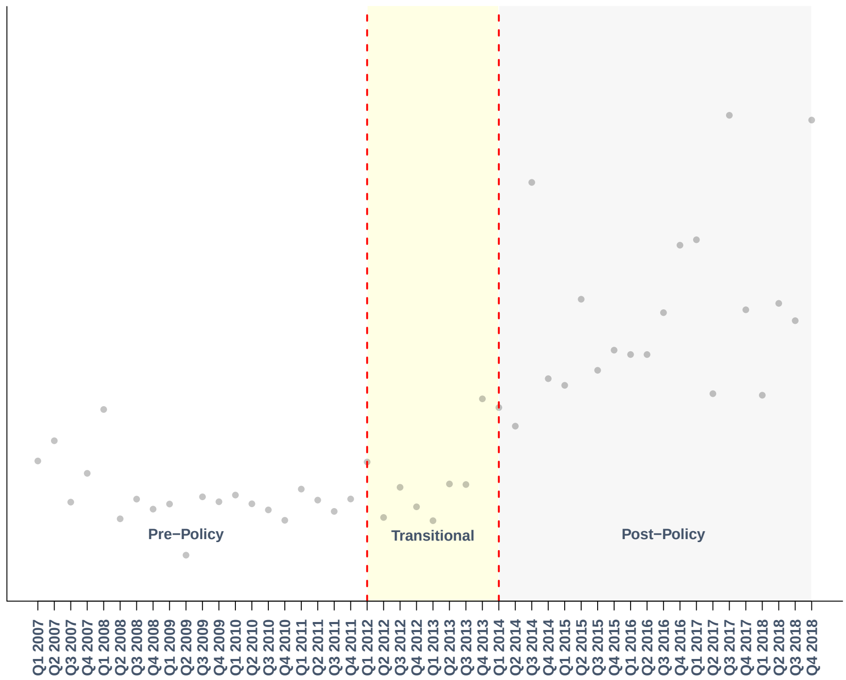

Figure 3.14: Representation of data segmentation applied in regards to all *ITS* analyses.

Segmented Regression

In **chapter 5** a segmented regression approach was undertaken, representing the standard methodology, in which a single *generalized linear model* was applied to the complete time series (Kontopantelis et al., 2015), utilising indicative variables to segment the differing periods during analysis (Huitema and Mckean, 2000). Prior to the identification of the appropriate approach to modelling the data, relevant tests were undertaken in regards to *seasonality* and *autocorrelation* using both the *seastest* package in *R* (Ollech, 2019) and *Durbin-Watson* test (Tillman, 1975) respectively.

The intervention effect was subsequently calculated as the difference between the slopes and intercepts of the models fit to the *pre-* and *post-policy* periods

(Wagner et al., 2002; Beard et al., 2019), including a separate transitional period (Lane and Hall, 2019) [equation 3.8].

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 + \beta_3 + \beta_4 X_t \tag{3.8}$$

In the above equation (based upon Wagner et al. (2002); Lopez Bernal et al. (2018); Hudson et al. (2019)), Y_t is the estimated intervention effect at quarter t; β_0 constitutes the modelled baseline level (the *pre-policy* intercept); β_1 can be considered to represent the rate of change in area between each quarter of the *pre-policy* period (the *pre-policy* trend); T denotes the '*Time*' identifier (relating to quarters); β_2 corresponds to the level change which occurs between the *pre-policy* and transitional periods; β_3 the level change between the transitional and *post-policy* periods; β_4 represents the difference between the rate of change in area in the *post-policy* period when compared to the *pre-policy* equivalent (the change in trend); and X designates the dummy '*Trend*' variable.

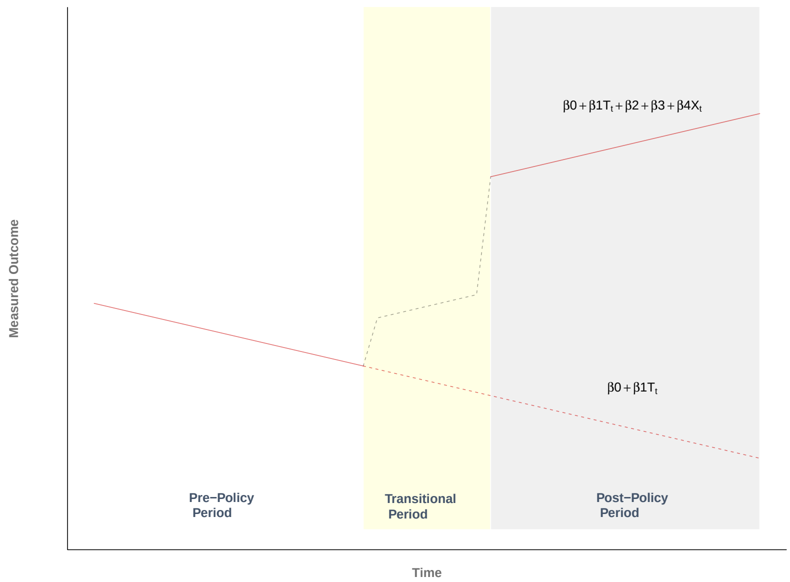

Figure 3.15: Graphical representation of intervention effects model.

Forecast Modelling

In **chapters** 5 and 6 an alternative approach to *ITS* was undertaken, whereby an appropriate model was separately fit to the *pre-policy* period, from which forecast, synthesised counterfactual estimates could be derived in regards to the *post-policy* period (Linden, 2018).

In relevant literature pertaining to the *forecast approach* the *pre-intervention* segment is commonly modelled using either *ARIMA* or *Holt-Winters* methods (Linden, 2018; Bridge et al., 2020). However, in this analysis a *dynamic linear model* was utilised as an alternative, primarily as the data did not consist of a suitable number of observations to meet the recommended minimum required for ARIMA modelling [cited as *50* or greater] (Chen et al., 2008) and due to practical advantages over comparable *Holt-Winters* exponential smoothing (Roberts, 1982), such as their suitability to modelling short time series and incorporation of uncertainty (Michel and Makowski, 2013).

This method can be considered a manual replication of the core functions which underpin the *Causalimpact* package (Brodersen and Hauser, 2020) used in (Ramachandra, 2019).

Dynamic Linear Models allow for the regression coefficients to change over time and are recognised as being useful in analyses of time series derived from environmental data, where the underlying drivers of events may not exert a constant influence (Laine, 2020). Crucially, they are capable of modelling non-stationary data (West, 1995) and account for autocorrelation and cyclical components, whilst being applicable to short time series with limited observations (Fei et al., 2011). Consequently, it was deemed appropriate to model the 20 observations which constituted the *pre-policy* period.

Relevant *dynamic linear model* programming was undertaken within *R*, using the dedicated *dlm* package, which provides a flexible framework suitable for both simple and complex state space structures (Petris and An, 2010), including non-gaussian and non-linear data (Petris et al., 2009). The *package* includes a specific function through which to estimate unknown model parameters, based upon maximum likelihood (*dlmMLE*) (Petris and Petrone, 2011) and the capacity to estimate future values and variance (*dlmForecast*) both of which were utilised in this research.

In regards to the Forecast model *ITS* approach the intervention effect should be considered to reflect the absolute differences between the modelled *post-policy* period and predicted counterfactual values at times

$t_{+28}, t_{+29}, ...t_{+47}$ (Mohr, 1995; Wagner et al., 2002; Shin, 2017; Linden, 2018).

Due to the uncertainty built into the synthesised counterfactual by the model, derived values are reported as an estimated 'minimum intervention effect', based upon the difference between relevant modelled values and the corresponding upper or lower threshold of the 95% prediction interval [figure 3.16] (Lin and Liu, 2005).

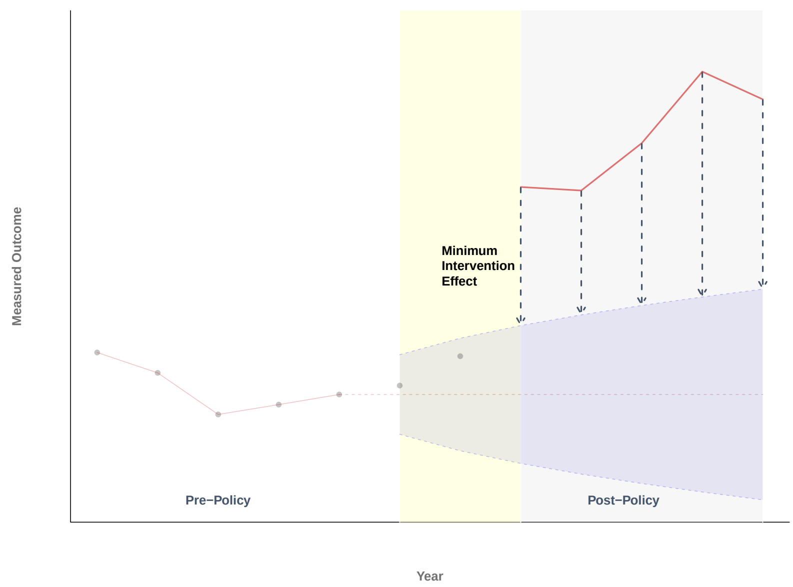

Figure 3.16: Graphical representation of estimated minimum intervention effect using annual data.

CHAPTER 4

Illusions of Space

Analysing Temporal Patterns in Green Space

"*The village of Shottery, a hamlet of Stratford, is, altogether, much the same as it must have been at that sunny time in the Poet's life when, after the exit of the school-boy , he trod the stage of the world as the lover. And the fields through which the footpath leads, the hedges, the stiles, and the general aspect of the place, are perhaps now, much the same as they were three centuries ago.*"

Remarks on Shakespeare

Smith (1877)

To some extent the rural landscape around *Shottery* to which *Smith (1877)* alluded, had remained largely untouched in the succeeding hundred years. Whilst the expansion of the village through the Nineteenth and Twentieth Centuries had consumed much of the undeveloped land to the North and East (Stratford-on-Avon District Council, 1992), the extensive green pasture land to the West, which once constituted part of the *Hewlands Farm* estate had been retained in much its original form recorded in 1543.

Despite pressure to deliver additional land for the development of accommodation, the submission of plans to convert the patchwork of fields to large-scale housing (Boyer, 2009) was rejected by *Stratford-on-Avon Council* in 2011 (Stratford-on-Avon Council, 2011). In arriving at this decision it was adjudged that the damage to the rural aesthetic of the village and in particular to the estate associated with the Grade 1 listed *Anne Hathaway's* cottage, was substantial (Stratford-on-Avon Council, 2011). As such, the proposal was deemed to contravene the Local Authority's District Plan (1996 - 2011).

The subsequent appeal, submitted by the applicant in 2012, would become the subject of one of the most important test cases for the planning framework introduced by the Coalition Government earlier in the year (Geoghegan, 2013) and was appropriated as a symbol of the existential, environmental threat it posed (CPRE, 2013).

The Secretary of State For Communities and Local Government overturned the decision, allowing 800 homes and associated infrastructure to replace the 54.81 Hectares of agricultural land (DCLG, 2012b) against the will of the Local Authority. Citing the failure of *Stratford-on-Avon Council* to identify adequate land to meet evidentially valid housing need as a material consideration (DCLG, 2012b), the case reportedly set precedence for interpretation of the provisions within the *National Planning Policy Framework* (Geoghegan, 2013).

The loss of green space to urban development is commonly portrayed as relating to a variety of driving forces (Hersperger et al., 2018). However, the role of policy in the protection of natural land remains relatively under-explored (Bürgi et al., 2005). Examples of the chronology associated with the *Shottery* site can therefore be deemed indicative of the underlying relationship between policy and land.

4.1 Introduction

Through legislative and policy interventions, national governments are assumed to play a significant role in the shaping of land cover and land use (Garcia-Martin et al., 2020). With the regulation of land loss representing one of the motivating factors behind the evolution of planning policy (Cullingworth and Nadin, 2003; Nuissl and Siedentop, 2020). As the retention of natural and semi-natural surfaces has become politically recognised as integral to both global and local environmental commitments (Bulkeley et al., 2011), the development of a conceptual model relating to the role of policy has come to constitute a research imperative (Hersperger et al., 2018; Morrison and Pearce, 2000).

Similarly to other policy fields, it is contended the determination of the relationship between policy interventions and outcomes requires robust quantitative analyses (Fischer and Miller, 2017; Plieninger et al., 2016) founded upon *ex post facto* impact evaluation of substantive examples (Shahab et al., 2019). However, research describing this relationship remains limited, largely associated with a methodological discord between policy and land science scholars, in regards to the extent to which quantitative data can encapsulate the complexities inherent to the planning system (Hersperger et al., 2018).

Whilst research has evolved around single types of land use (commonly 'natural' land (Bengston et al., 2004; Dallimer et al., 2011; Kasraian et al., 2019; Mu et al., 2016)) as functional indicators of policy effects (Hersperger et al., 2018; Morrison and Pearce, 2000), methods have generally reflected the occurrence of change between two distinct points with lengthy time intervals (Kasraian et al., 2019; Mu et al., 2016) or patterns of development throughout a post policy period (Dallimer et al., 2011). To date, no studies have sought to investigate whether green space data covering a continuous period between two distinct policy agendas can be used to discern a point after which an effect appears evident. The establishment of such can be considered a core element in the advancement of the conceptual model as it can offer a more nuanced insight in regards to the process underlying change (Awe et al., 2020).

The outlined research gap can largely be associated with three issues inherent to data sources. Although taken at regular intervals, developing a consistent temporal range through satellite imagery can be restricted where land cover is obscured by climatic conditions (such as cloud shadow or solar haze) (Asner, 2001; Kirui et al., 2013). It is further complicated by a dependence upon large amounts of data, requiring significant processing power. Consequently, it is generally impractical to acquire data relating to a continuous period (Kasraian et al., 2019). This can be considered to have influenced analyses of secondary data, in which assumptions related to the extended time frames between a policy instrument being introduced and evidence of its effect are subject to similar *pre-post* methods (Ganser and Williams, 2007).

Furthermore, the identification of land change is highly influenced by both the resolution of data and homogeneity of land surface, which influence the contrast between different land types (Horning and DuBroff, 2004). For example, if an area of verdant forest is cleared and replaced with an artificial concrete surface, the contrast between the original green pixels and subsequent grey is easily discerned (Erener and Düzgün, 2009). However, the conversion of an area of allotment to pre-development construction site would be less simply identified as land use change. Thus, change based upon remote sensed data primarily equates to large area conversion between 'natural' land and completed built development (Turner et al., 2015), which is subject to significant time lags (Lichfields, 2016).

Finally, there is a need for data to relate to the transition between two policy approaches within the context of a planning system, which is shown to be highly responsive to policy change (Morrison and Pearce, 2000; Shahab et al., 2019). Where Kasraian et al. (2019) evidenced a zoning system to be subject to prolonged legacy effects, in which previous policy approaches continued to influence patterns of development, Dallimer et al. (2011) reported the discretionary system operated in England to be responsive to policy.

In light of both the availability of uninterrupted, alternative data sources (Plieninger et al., 2016) and anticipated suitability of the example (Dallimer et al., 2011), the research adopted a case study derived from contemporary policy reform within England. Under the Conservative led coalition government of 2010 to 2015, fundamental reforms of national planning policy were introduced in the form of the *Localism Act 2011* and *National Planning Policy Framework* (Davoudi, 2011). It was contended that considerable provisions which had previously directed development away from green space were weakened (Sibley-Esposito, 2014). As a result of which it was suggested the loss of undeveloped land would increase (Gosden, 2014). However, despite a strong *a priori* basis for the proposed effect, negligible research had been undertaken to empirically investigate the validity of such (CPRE, 2018).

4.1.1 Primary Research Aim

Accordingly, this research aimed to investigate the extent to which novel data and analytical methods could be used to discern impacts upon land associable with policy change. It aimed to develop the first quantitative evidence of the effects associated with the transition between two distinct policy frameworks based upon a continuous time period. Through which it could be used to augment existing knowledge pertaining to the dynamic relationship between planning policy as a regulatory agent and land use change (Hersperger et al., 2018). By undertaking analysis which related to the period subsequent to that which informed Dallimer et al. (2011) it builds towards a coherent picture of continuous land use change under different types of policy within the context of the discretionary system operated in the United Kingdom.

Despite significant media scrutiny (Gosden, 2014; Watts, 2017), the extant debate around the developmental threat to green space associated with *Localism Act 2011* and *National Planning Policy Framework* (2012) has not been supplemented by formal statistical analysis and offers a germane case study.

It is therefore the primary aim of this research to address the outlined issue through investigation of the area of green space identified as being subject to development across a consistent period accounting for the previous and revised policy frameworks.

In seeking to do so, the following research question is explored to test the hypothesis that:

> *the area of green space land which underwent development in the period after the implementation of the revised policy framework was greater than that which occurred in the period prior.*

Research Question 1: Has the area of green space which was subject to development evidenced alteration in rates which could be associated with the adoption of the *Localism Act 2011* and *National Planning Policy Framework (2012)*?

4.1.2 Contribution

Through the novel application of a *change point detection* method to quarterly land change data this research identified a time period after which the rate of development on green space land underwent a structural shift, based upon the example of the *Localism Act 2011* and *National Planning Policy Framework*. In so doing it can be considered to both corroborate reported concerns related to the revised framework (Sibley-Esposito, 2014) and offers a data-driven methodology through which to associate land change with national planning policy.

Consequently, this research can be considered to address the need for alternative data sources to be utilised in regards to analysis of underlying drivers (Plieninger et al., 2016) and applied a robust method which can advance understanding of the conceptual model relating to the role of national policy as a regulator of land use (Hersperger et al., 2018; Morrison and Pearce, 2000; Shahab et al., 2019).

It represents the first analysis of the impact attributable to the *Localism Act 2011* and *National Planning Policy Framework*, enhancing the ongoing debate (CPRE, 2018; Gosden, 2014; Sibley-Esposito, 2014). Whilst, to the researchers knowledge being the only use of *change point detection* in relation to planning policy and enhancing its limited prior application within the context of policy more generally (Friede et al., 2006). Thus, offering an example of the methods potential to discern a policy impact based upon an indicative variable.

4.1.3 Chapter Structure

The sample of Local Authority Areas, which underpin the research is detailed in **section 4.2.1**. After which both the temporal range [**4.2.2**] and dependent variables [**4.2.3** and **4.2.4**] are described. Both initial exploratory analysis [**4.2.5**] and *change point detection* [**4.2.6**] methodologies are outlined. Results are presented in regards to each approach in **section 4.3** and a discussion is examined in **section 4.4**. Finally, conclusions are drawn around the implications of the research [**4.5**].

4.2 Methods

This chapter consists of two cognate methodological approaches, the first of which seeks to apply techniques pursuant to exploratory analysis intended to inform subsequent analytical methods (McCue, 2014). The second, reflects the application of a *change point detection* method as a means through which to identify the existence of a temporal event after which the data profiles diverged (Killick et al., 2012), previously established in regards to land change in Ramachandra (2019).

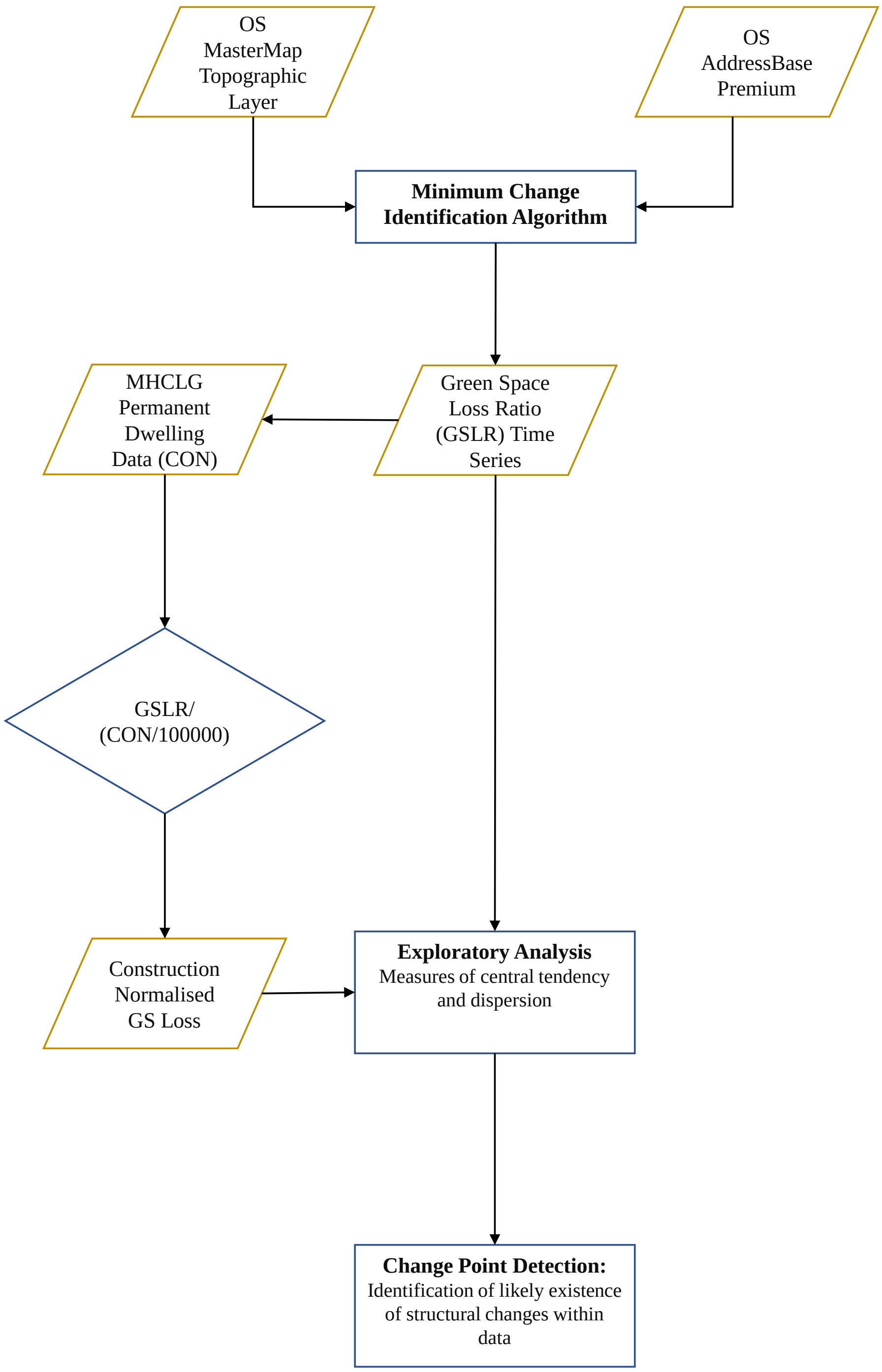

Figure 4.1: Outline structure of methodological approach.

4.2.1 Sample

Consistent with the previously outlined methodology, the research undertaken in this analytical chapter is derived from the complete sample of 42 Local Authority areas identified in **section** 3.3. Said sample comprises an equal distribution of 21 urban and 21 rural authorities (figure 4.2), obtained from a maximum variation sampling technique [refer to 3.3].

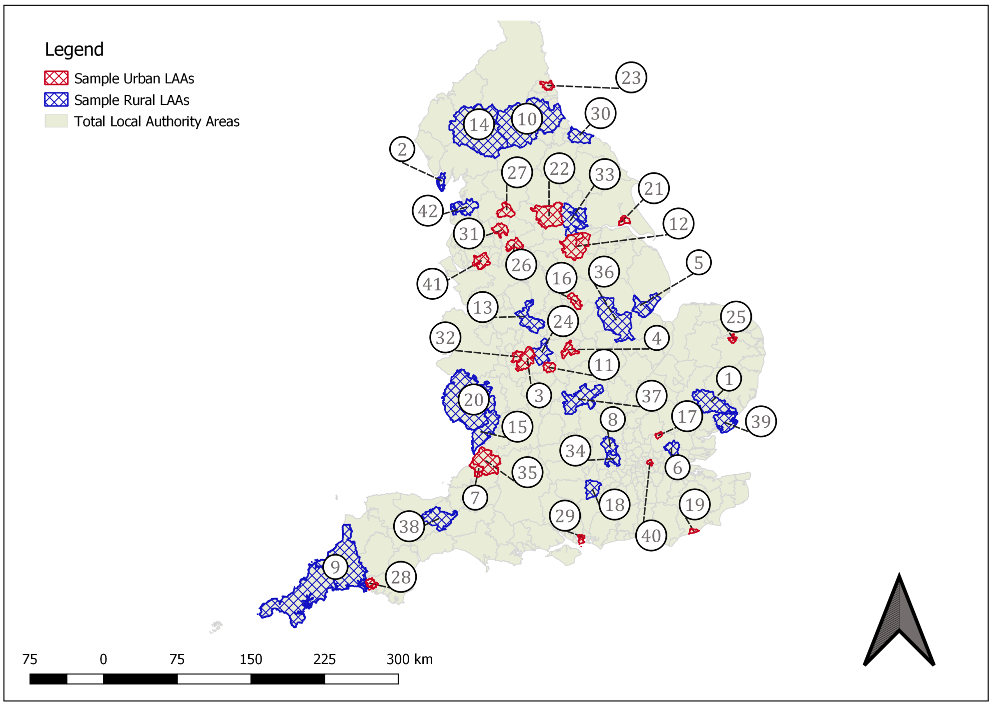

Figure 4.2: Source: Ordnance Survey (2018b)
Distribution of sample Local Authority Area, with 'rural' LAAs identified in blue and 'urban' identified in red.

1	Babergh	**15**	Forest of Dean	**29**	Portsmouth
2	Barrow-in-Furness	**16**	Gedling	**30**	Redcar and Cleveland
3	Birmingham	**17**	Harlow	**31**	Rossendale
4	Blaby	**18**	Hart	**32**	Sandwell
5	Boston	**19**	Hastings	**33**	Selby
6	Brentwood	**20**	Herefordshire, County of	**34**	South Bucks
7	Bristol, City of	**21**	Kingston upon Hull, City of	**35**	South Gloucestershire
8	Chiltern	**22**	Leeds	**36**	South Kesteven
9	Cornwall	**23**	North Tyneside	**37**	South Northamptonshire
10	County Durham	**24**	North Warwickshire	**38**	Taunton Deane
11	Coventry	**25**	Norwich	**39**	Tendring
12	Doncaster	**26**	Oldham	**40**	Tower Hamlets
13	East Staffordshire	**27**	Pendle	**41**	Warrington
14	Eden	**28**	Plymouth	**42**	Wyre

Table 4.1: Reference Table: Local Authority Area samples

Based upon the identification of green space as any land polygon classified as 'natural' by OS (Barbosa et al., 2007; Davies et al., 2008), a cumulative area of 1,658,460 Ha was recorded across the 42 sample authority areas in 2007, representing the baseline in regards to which subsequent data is framed.

Therefore, within the context of the data, in 2007 green space could be considered to constitute *82.85%* of the total area (2,001,792 Ha) [including bodies of water]. This compares to the National scale, where the total green space area was recorded as around 90% in both 2005 (Office of the Deputy Prime Minister, 2006) and 2011 (Watson and Albon, 2011).

However, significant differences were evident in relation to each of the authority areas, with both the smallest area and proportion of green space relating to Tower Hamlets, where just 101.46 Ha of green space comprised *5.13%* of the total Local Authority Area. Whilst the largest area of green space was recorded in regards to Cornwall, which contained 277,254.40 Ha, the area in which green space accounted for the highest proportion of total area was Eden, at *95.83%*.

Clear distinctions can be drawn between the profiles of 'rural' and 'urban' LAAs. The 21 authorities which can be broadly categorised as 'rural' comprised a total area of 1,656,565 Ha, of which **1,447,918 Ha** (*87.40%*) was recorded as green space. Respective means for the area of green space for each authority and its proportional equivalent, were reported as **68,948.47 Ha** and *84.31%* [table 4.2].

For the 'urban' comparators, the total area of 345,227.4 Ha, contained **210,541.8 Ha** (*60.99%*) of green space. Both the mean area of green space and percentage of total area, per authority were significantly smaller than the 'rural', at **10,025.8 Ha** and *46.41%* [table 4.2].

	Urban		Rural	
Total Area (Ha)	345,227.40		1,656,565.00	
Area of Green Space (Ha)	210,541.80	[*60.99%*]	1,447,918.00	[*87.40%*]
Mean Area Green Space per LAA (Ha)	10,025.80	[*46.41%*]	68,948.47	[*84.31%*]

Table 4.2: Summary of sample Local Authority Area green space profiles.

4.2.2 Temporal Range

Throughout this section of research all data relates to a continuous period between the start of January 2007 and end of December 2018. Therefore, consisting of 4 years (2007 - 2010) or 19 complete quarters (Q1 2007 - Q3 2011) prior to the commencement of the first relevant legislative provisions (*Localism Act 2011. [s.240]*) in November 2011; 2 years (2011 and 2012) or 2 quarters (Q4 2011 and Q1 2012) during which relevant provisions came into force; and 6 years (2013 - 2018) or 27 quarters (Q2 2012 to Q4 2018) after which both were in operation.

4.2.3 'Green Space Loss'

In regards to both analytical methods utilised within this research, '*green space loss ratio*' data was adopted as the primary green space loss metric.

Therefore, data represent two univariate time series, reflecting separately the cumulative area of green space on which data indicated development had occurred (as a proportion of the total available area of green space at said time) per annum and per quarter. Accordingly they can both be understood to reflect the annual or quarterly sum derived from the spatial intersection between parcels of land which were recorded as green space in one time ($t-1$) and the succeeding 'developed' form in time (t) (where $t = 0, ..., +11$ for annual data and $t = 0, ..., +47$ for quarterly data).

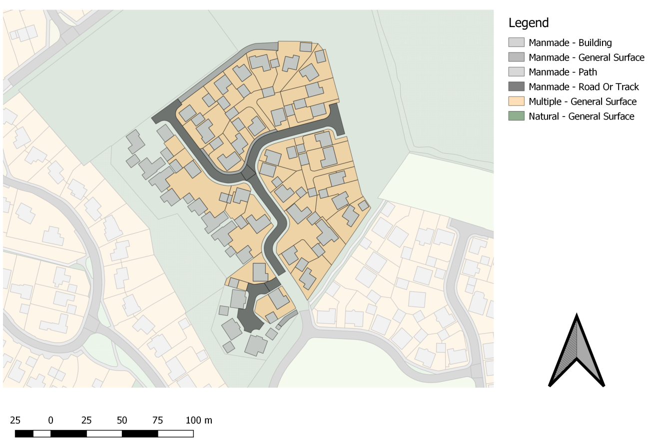

Figure 4.3: Data Source: Ordnance Survey (2018b)
An example of an individual polygon reflecting 'green space loss' data.

For example, t_0 in the quarterly data represents the cumulative area of green space from quarter 1 of 2007, on which either a building and relevant infrastructure or preparatory site development was recorded as having occurred in quarter 2 of 2007.

Data was retained as an annual variable for the purpose of initial exploratory analysis, as a way to adhere to the temporal ranges applied in commensurate research (primarily (Dallimer et al., 2011)). However, in order to adhere to relevant minimum recommendations in regards to temporal analyses (Jandoc et al., 2015; Jebb et al., 2015; Zhang et al., 2011) the quartered subset was adopted for *change point detection*.

4.2.4 Confounding Variables

A full description of the rationale behind the adoption of confounding variables can be found in **section 3.4.2**.

To mitigate against the potential confounding influence of economic drivers of land change (Morrison and Pearce, 2000), particularly associated with the effects of the global financial crisis and subsequent recession upon rates of construction (Tatliyer, 2017), '*construction normalised green space loss*' equivalents were also analysed.

Said data can be understood as the '*green space loss ratio*' (m^2/Ha) per 100,000 newly built houses within the same time period. Consistent with '*green space loss ratio*' data, the '*construction normalised*' equivalents comprise two univariate time series of 12 and 48 observations, representing annual and quarterly loss respectively.

4.2.5 Exploratory Data Analysis

As an initial stage of analysis, a variety of descriptive, summary statistics were calculated in conjunction with visual inspection of a simple plot based upon the annual '*green space loss ratio*' data. Relevant data were considered as two segmented time series, representing a priori defined *pre-* and *post-policy* intervention periods, simply partitioned around the year 2012, during which the policy framework changed. Thus replicating the standard approach to segmentation (Dallimer et al., 2011; Ganser and Williams, 2007; Mu et al., 2016).

Accordingly, the first segment [*pre-policy*] refers to the inter-annual changes between 2007 and 2011, whilst the second [*post-policy*] encompasses 2012 through to 2018. It should be noted whilst a revised *NPPF* was published in July 2018 it was not considered likely to impact upon the data used in this research due to the 6 month delay in the *Ordnance Survey* revision policy (Ordnance Survey, 2009).

This preliminary approach is deemed fundamental to subsequent analyses (McCue, 2014), establishing a core understanding of the data through the identification of distributions, trends and patterns (Nick, 2007). Accordingly, analysis includes the most common statistics, with measures of central tendency (Weisberg and Weisberg, 1992), through arithmetic mean and median values (Thompson, 2009); measures of dispersion, including ranges, variance and standard deviation (Fisher and Marshall, 2009); and distributions or frequencies (Nick, 2007).

4.2.6 Change Point Detection

The methodology outlined within this section relies upon core functions from the *changepoint* package in *R* (Killick and Eckley, 2014).

Change Point Detection refers to methods intended to identify abrupt variations in time series, which imply the occurrence of some event which has altered the process generating the data (Aminikhanghahi and Cook, 2017).

A *Maximum log likelihood* estimation method was adopted, allowing for the identification of multiple change points based upon both mean and variance (Killick and Eckley, 2014). Broadly, a change point can be understood to reflect any quarter in which the sum of the negative log-likelihood of the test statistic (mean and variance of green space variables) derived from the segment of data up to and including that point and the succeeding segment exceed a defined penalty value (which is dependent upon the number of change points) [equation 4.1].

$$\min_{k,\tau}\left\{\sum_{i=1}^{k+1}[-l(z_{\tau_{i-1}:\tau_i})] + \lambda f(k)\right\} \tag{4.1}$$

Relating to a number of prospective change points identified as k, with positions $\tau = (\tau_0, \tau_1, ..., \tau_{k+1})$, where $\tau_0 = t_0$ and $\tau_{k+1} = t_{+47}$, z reflects the mean and variance of the dependent green space variable, λ is a fixed penalty value and f a penalty function.

Relevant penalty values between 1 and 100 were sequentially tested in advance based upon the *Change of Points for a Range of PenaltieS* [*CROPS*] algorithm (Haynes et al., 2017). As a result of which the optimal number of change points were identified using in-built diagnostic plot functions (Killick et al., 2012). A list of all penalty values was also derived, with the maximum value reflecting that which would produce one change point and the second highest the maximum at which multiple changes would be detected.

Using the *Pruned Extract Linear Time* algorithm (Killick et al., 2012) separate analyses were run for the following time series;

- Full sample '*Green Space Loss Ratio*'
- Rural subset '*Green Space Loss Ratio*'
- Urban subset '*Green Space Loss Ratio*'
- Full sample '*Construction Normalised Green Space Loss*'
- Rural subset '*Construction Normalised Green Space Loss*'
- Urban subset '*Construction Normalised Green Space Loss*'

As an initial element of analysis the *PELT* algorithm was run with a penalty set to the optimal value identified in the previous step. Where a single change point was detected the algorithm was subsequently rerun with the penalty value set to the maximum at which multiple change points were detected. Conversely, in instances where multiple change points were detected in the optimal scenario, the penalty was reset to its maximum value (at which a single point would be detected).

Derived results accordingly report mean and variance associated with the optimal change points and compare outcomes from alternative penalty values.

4.3 Results

4.3.1 Exploratory Data Analysis

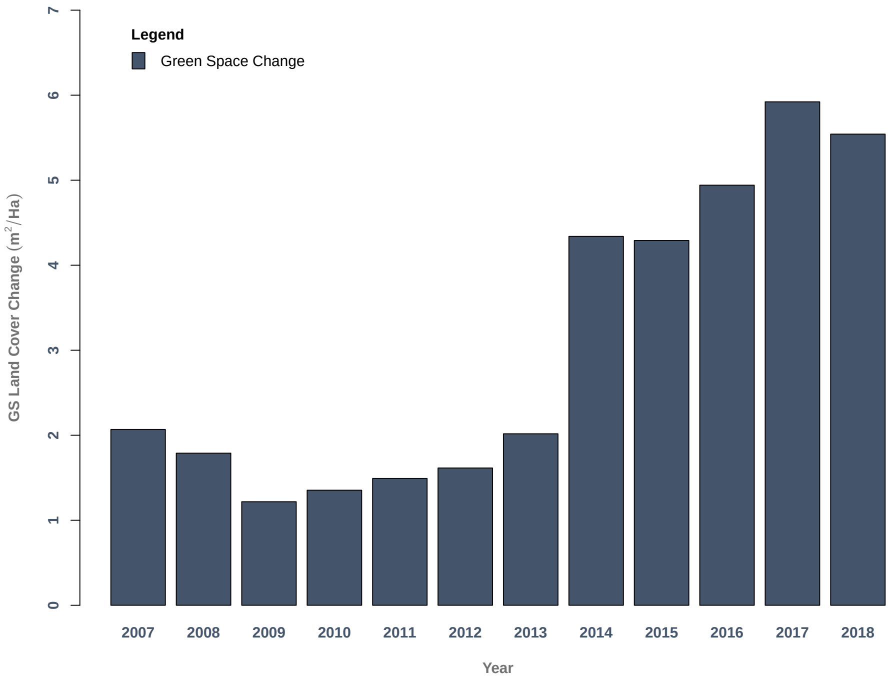

Figure 4.4: Raw *green space loss ratio* data rendered as bar plot

Year	Total Area Recorded as Green Space (2007 - Green Space Loss) (Ha)	Total Area of Green Space (m^2)	'Green Space Land Cover Change Ratio' (m^2/Ha)
2007	1658459.64	3430526.33	2.07
2008	1658116.59	2966475.54	1.79
2009	1657819.94	2019838.17	1.22
2010	1657617.95	2243564.77	1.35
2011	1657393.60	2473118.69	1.49
2012	1657146.29	2675914.29	1.61
2013	1656878.69	3342817.55	2.02
2014	1656544.41	7188287.18	4.34
2015	1655825.58	7105202.00	4.29
2016	1655115.06	8178600.44	4.94
2017	1654297.20	9797195.04	5.92
2018	1653317.48	9162822.98	5.54

Table 4.3: Green space loss data. Table reflects the total area of green space in each year, the total area of green space recorded as having undergone development and the derived '*green space loss ratio*' based upon the two prior columns.

Initial interpretation of the graphical representation of the data suggested the existence of different data profiles within the time series. The evident decline in the area which underwent development between 2007 and 2009 followed by the subsequent increase between 2010 and 2013 could be considered to potentially reflect the influence of economic effects upon the data. Whilst the existence of five consecutive years in which the area was notably higher than at any previous point were deemed to substantiate the need for further analysis.

The simple arithmetic average per-annum area of green space loss which occurred during the *pre-policy* period (2007 to 2011) was recorded as **1.58m^2/Ha**, with an associated standard deviation of 0.34. Whereas during the *post-policy* comparative period (2012 to 2018) it had more than doubled (*158.50%*) to **4.10m^2/Ha**, in conjunction with a much larger standard deviation of 1.67.

Relative median values were calculated as **1.49m^2/Ha** in regards to the *pre-policy* period, compared to **4.34m^2/Ha** following the implementation of the revised policy framework. The difference between the two periods could be considered to equate to a *190.81%* increase. In regards to each of these two main summary statistics the post-policy segment evidenced discernible increases upon the pre-policy equivalents.

Between 2007 and 2011 (*pre-policy*) the range was just **0.85m^2/Ha**, derived from a minimum value of **1.22m^2/Ha**, which was recorded as the change which occurred in 2009, and maximum of **2.07m^2/Ha**, relating to 2007. Whereas, the equivalent *post-policy* period saw greater variation, with a range of **4.31m^2/Ha**, relating to values of **1.61m^2/Ha** (2012) and **5.92m^2/Ha** (2017) [table 4.4].

	2007 - 2011	2012 - 2018
Mean (m^2/Ha)	1.58	4.10
Standard Deviation (m^2/Ha)	0.34	1.67
Median (m^2/Ha)	1.49	4.34
Range (m^2/Ha)	0.85	4.31

Table 4.4: Mean, Standard Deviation, Median and Range for full sample '*green space loss ratio*' data.

In accordance with the assumption that rates of development could be influenced by economic circumstance it was deemed notable the maximal value in the *pre-policy* period occurred in the single year prior to the financial crisis and the minimum was recorded in 2009. However, across the two time series it was also identified that the values recorded in regards to five of the seven intervals during the indicative *post-policy* period exceeded the maximum area in the *pre-policy* segment, from 2014 to 2018 consecutively.

Visualised as violin plots (Hintze and Nelson, 1998) [figure 4.5], the two periods appear to reflect very different data profiles, with the *pre-policy* period loosely resembling a *Gamma* distribution, whilst the *post-policy* can be characterised as minimally *bimodal*. The slightly bimodal distribution of the *post-policy* period may be considered to imply that it incorporates data related to two distinct variables, supporting the hypothesis that the effects of planning policy reform may take up to two years to become evident in rates of development (Shelter, 2019).

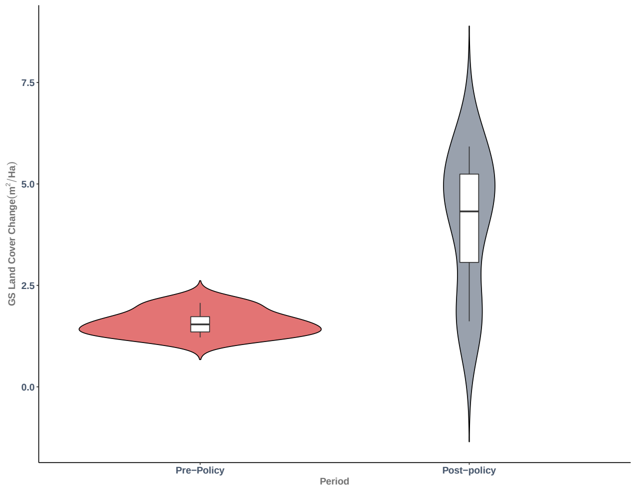

Figure 4.5: Violin plots for the segmented *pre* and *post* policy periods.

In relation to the '*construction normalised*' equivalent data, relevant summary statistic continued to evidence material differences between the two originally defined periods. For every 100,000 residential developments which were undertaken in the *post-policy* period an average green space area of **17.98m^2/Ha** (standard deviation of 5.80) underwent transition to developed form. This figure represented a *115.23%* increase upon the relative value of **8.35m^2/Ha** (standard deviation of 1.32) recorded in the *pre-policy* period.

The difference between medians grew to *157.56%*, derived from values of **7.66m^2/Ha** in the *pre-policy* period and **19.73m^2/Ha** in the *post*. Whilst the respective ranges were recorded as **2.90m^2/Ha** (*pre-policy*) and **14.37m^2/Ha** (*post-policy*) [table 4.5].

	2007 - 2011	2012 - 2018
Mean (m^2/Ha)	8.35	17.98
Standard Deviation (m^2/Ha)	1.32	5.80
Median (m^2/Ha)	7.66	19.73
Range (m^2/Ha)	2.90	14.37

Table 4.5: Mean, Standard Deviation, Median and Range for full sample '*construction normalised green space loss*' data.

During the *pre-policy* period the smallest annual area of green space loss (per 100k residential developments) occurred in regards to 2007. However, contrasting starkly with the raw data, in both 2008 and 2009 the largest two areas of change were recorded for the first segment. The *post-policy* period was again defined by values in excess of the maximum recorded prior to 2012 in every year between 2014 and 2018.

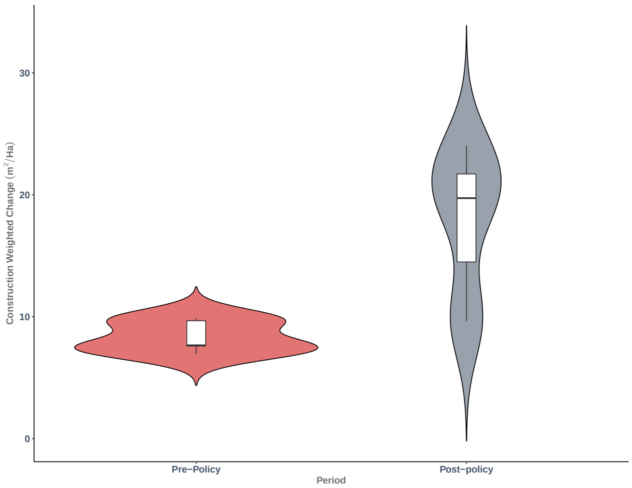

Figure 4.6: Violin plots for the '*Construction normalised*' segmented *pre* and *post* policy periods.

The distributions of both the *pre-* and *post-policy* periods remained broadly similar to the raw data [figure 4.6]. This remained suggestive of the two periods being characterised as having come from different populations and could be considered to support the potential existence of a structural change existing within the data.

To investigate further, the pre-policy and post-policy periods were redefined as 2007 to 2013 and 2014 to 2018 respectively. Means of **1.65m^2/Ha** (sd of 0.32) and **5.00m^2/Ha** (sd of 0.72) were recorded based upon the '*green space loss ratio*' data. Reflecting an increase in mean of *203.36%* and difference in standard deviation of 0.4. Whilst the median in the pre-policy period (2007 to 2013) was *206.01%* lower than the equivalent post-policy value (**1.61m^2/Ha** and **4.94m^2** respectively). Rates of recorded green space loss within the revised pre-policy period were within **0.85m^2/Ha** of each other, from **1.22m^2** to **2.07m^2**. This was identical to the original pre-policy period (2007 to 2011), with the values recorded for 2012 and 2013 residing within the prior range. However, the range in the revised post-policy period was **1.44m^2/Ha**, showing a greater degree of consistency throughout the segment [table 4.6].

	2007 - 2013	2014 - 2018
Mean (m^2/Ha)	1.65	5.00
Standard Deviation (m^2/Ha)	0.32	0.72
Median (m^2/Ha)	1.61	4.94
Range (m^2/Ha)	0.85	1.44

Table 4.6: Mean, Standard Deviation, Median and Range for full sample '*green space loss ratio*' data. Revised *pre* and *post-policy* periods.

Updated means derived for the '*Construction normalised*' data evidenced a *141.91%* increase between the two periods (**8.78m^2/Ha** and **21.23^2**), with relative standard deviations of 1.30 (pre-policy) and 2.02 (post-policy). The medians reflected a *118.34%* difference between the two periods, based upon values of **9.66m^2/Ha** and **21.10m^2/Ha**. The redefinition of the pre-policy period resulted in a range of **3.05m^2/Ha**, derived from a minimum of **6.96m^2/Ha** and **10.01m^2/Ha**. In regards to the revised post-policy period the range of values was recorded as **5.05m^2/Ha**. This reflected a slight increase upon the original segment in relation to the pre-policy data, but a significant decrease where applied to the post-policy. Cumulatively, results obtained from the revised periods suggested the data could be characterised as reflective of two periods relating to 2007 to 2013 and 2014 to 2018 [table 4.7].

	2007 - 2013	2014 - 2018
Mean (m^2/Ha)	8.78	21.23
Standard Deviation (m^2/Ha)	1.30	2.02
Median (m^2/Ha)	9.66	21.10
Range (m^2/Ha)	3.05	5.05

Table 4.7: Mean, Standard Deviation, Median and Range for full sample '*construction normalised green space loss*' data. Revised *pre* and *post-policy* periods.

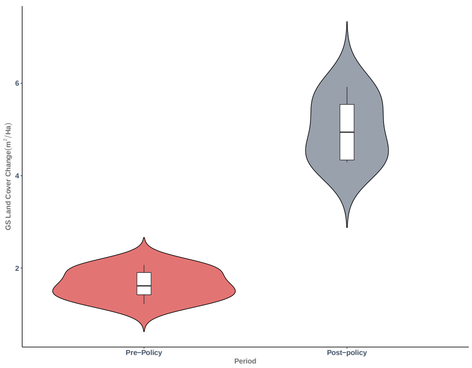

Figure 4.7: '*Green space loss ratio*' violin plots relating to revised *pre* (2007-2013) and *post* (2014 - 2018) policy periods.

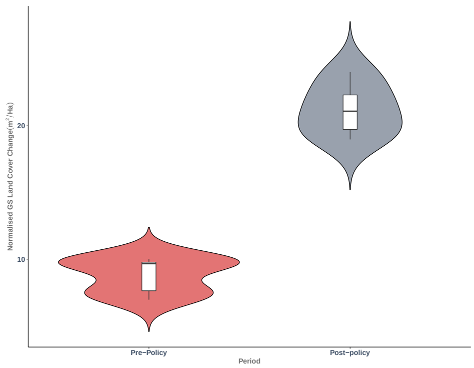

Figure 4.8: '*Construction normalised*' violin plots relating to revised *pre* (2007-2013) and *post* (2014 - 2018) policy periods.

The changes to the distributions between the original and revised policy periods were interesting [figure 4.7 and 4.8]. Whilst the distribution of the '*green space loss ratio*' pre-policy data was similar to under the original segmentation, the post-policy period evidences reduced dispersion. A similar effect was evidenced in regards to the '*construction normalised*' equivalent. However, the *pre-policy* segment appeared to suggest the existence of two distinct data profiles. In both instances the data appear to show divergent structures between the two periods.

Whilst not forming the core of this research, the outlined exploratory results suggested there were grounds to undertake more detailed analysis of the data using time series modelling methods, such as *change point detection*.

4.3.2 Change Point Detection

Based upon methods using both mean and variance, the null hypotheses (that no change had occurred within the data) were rejected in all instances, as the likelihood of the existence of a change point exceeded all logical penalty values.

In relation to the raw '*green space loss ratio*' data, calculations based upon mean and variance identified a single likely change point between quarters 3 and 4 of 2013. The maximum *log-likelihood ratio* statistic was recorded as *82.05*, which was derived from means and variance of *0.38* and *0.02* for the period prior to the identified change point and *1.19* and *0.16* after [table 4.8].

	Q1 2007 - Q3 2013	Q4 2013 - Q4 2018
Mean	0.38	1.19
Variance	0.02	0.16

Table 4.8: Summary of '*green space loss ratio*' mean and variance relating to the identified segments identified around the change point, based upon the optimal penalty value [82.05].

Prior diagnostic tests using the *PELT* algorithm identified the penalty value for a single change point as *82.05*. Whereas in order to identify multiple changes the relevant penalty would need to be reduced to *19.75*, in which case 3 change points were identified as quarter 3 of 2013, quarter 4 of 2015 and quarter 2 of 2016.

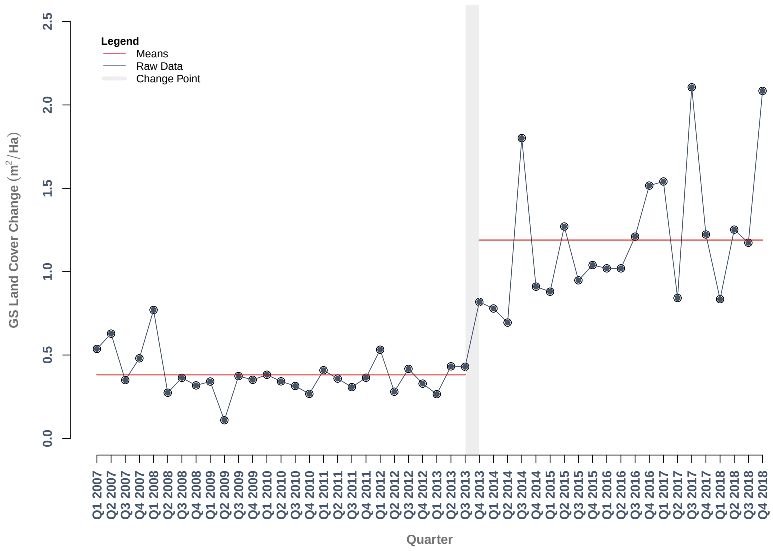

Figure 4.9: Change Point Detection: Raw '*green space loss ratio*'. A single change point was identified as having occurred between quarters 3 and 4 of 2013.

The identified change point was broadly consistent with the existence of a two-year lag between the approval of a planning application and subsequent completion of the approved development project (Shelter, 2019) [figure 4.9], which would imply that any effects associated with the revision of the planning system would not be evident until at least two-years after introduction.

Additional *change point detection* methods were separately run in regards to the 21 'urban' and 21 'rural' Authorities. The indicative 'rural' area analysis could be considered analogous with the overall data, but recorded a single change point as between quarter 4 of 2013 and quarter 1 of 2014 [table 4.9]. The calculated maximum *log-likelihood ratio* statistic was *81.57*. Relative means for the period prior to and after the change point were *0.23* and *0.72*, whilst variance was recorded as $<$*0.00* and 0.08 respectively.

	Q1 2007 – Q4 2013	Q1 2014 - Q4 2018
Mean	0.23	0.72
Variance	$<$ 0.00	0.08

Table 4.9: Rural Subset: Summary of '*green space loss ratio*' mean and variance relating to the segments identified around the change point, based upon the optimal penalty value [81.57].

In contrast the diagnostic plot for the 'urban' subset discerned two significant change points, which were identified as having occurred between quarters 1 and 2 of 2008 and quarters 3 and 4 of 2013. The respective mean and variance prior to quarter 2 of 2008 were *2.50* and *0.86*, whilst between quarter 2 of 2008 and quarter 3 of 2013 both had decreased to *1.05* and *0.11*, prior to a sharp increase from quarter 4 of 2013 where they reached *4.30* and *3.05* [table 4.10]. Interestingly, where the penalty value was increased (from the original *33.43* to *56.52*) to ensure the identification of a single change point only, it was identified as having occurred after quarter 3 of 2013.

	Q1 2007 – Q1 2008	Q2 2008 – Q3 2013	Q4 2013 - Q4 2018
Mean	2.50	1.05	4.30
Variance	0.86	0.11	3.05

Table 4.10: Urban Subset: Summary of '*green space loss ratio*' mean and variance relating to the segments identified around the change point, based upon the optimal penalty value [33.44].

As alluded to previously, it can be speculated the initial change point in 2008 may be attributable to a decline in rates of total development associated with the impacts of the 2008 to 2009 recession upon the construction sector (Edmund et al., 2009). As such consideration should be given to the extent to which the subsequent change point may reflect economic recovery rather than reflecting the altered policy circumstances.

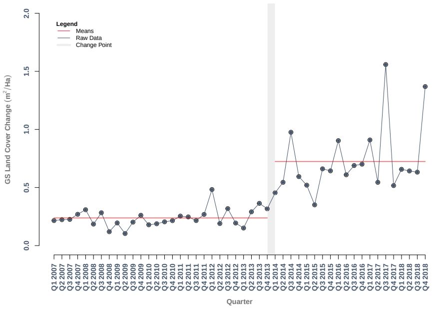

Figure 4.10: Graphical representation of Change Point Detection undertaken in regards to ‘rural’ Authority samples

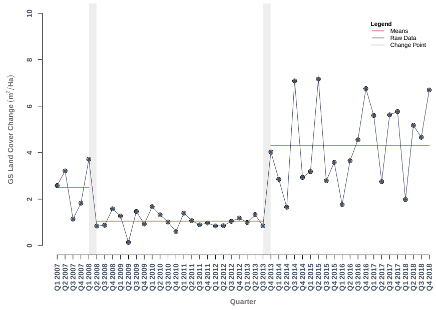

Figure 4.11: Graphical representation of Change Point Detection undertaken in regards to ‘urban’ Authority samples

A single change point between quarters 3 and 4 of 2013 was also identified in relation to the ‘*construction normalised data*’, based upon a maximum *log-likelihood ratio* of *61.86*. The means before and after the change point were recorded as *8.33* and *20.62*, whilst variance went from *8.60* to *33.64* [table 4.11]. Where the penalty value was reduced to *11.13* to allow for the existence of multiple change points, two were identified between quarters 1 and 2 of 2013 and quarters 2 and 3 of 2014. Notably, neither was within the indicative *pre-policy* period [figure 4.12].

	Q1 2007 - Q3 2013	Q4 2013 - Q4 2018
Mean	8.33	20.62
Variance	8.60	33.64

Table 4.11: Summary of ‘*Construction normalised green space loss*’ mean and variance relating to the identified segments identified around the change point, based upon the optimal penalty value [61.86].

Significantly, the outlined results could be interpreted as suggestive of economic circumstances not appearing to be the primary driver of change in regards to the aggregated data.

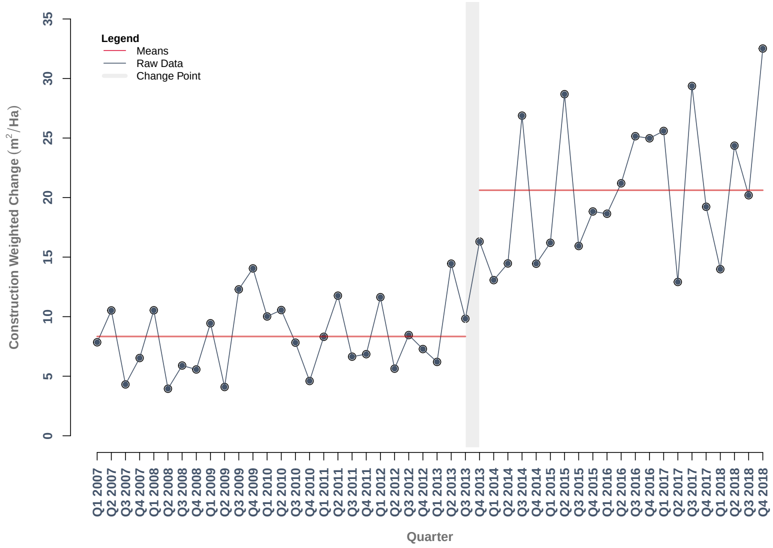

Figure 4.12: Change Point Detection: Raw '*green space loss*'. A single change point was identified as having occurred between 2013 and 2014.

However, where applied to 'rural' authorities only, two change points were discernible within the data, after quarter 3 of 2008 and quarter 1 of 2014 [figure 4.13]. Between quarters 1 of 2007 and 3 of 2008 the mean area of green space which underwent development was *9.59*, with a variance of *1.02*. In the second identified segment of the time series (Q4 2008 to Q1 2014) the respective means and variance had increased to *15.83* and *33.98*. Whilst from quarter 2 of 2014 the mean had become *29.60* and variance *73.17* [table 4.12].

	Q1 2007 – Q3 2008	Q4 2008 – Q1 2014	Q2 2014 - Q4 2018
Mean	9.59	15.83	29.60
Variance	1.02	33.98	73.17

Table 4.12: Rural Subset: Summary of '*Construction normalised green space loss*' mean and variance relating to the segments identified around the change point, based upon the optimal penalty value [23.79].

The outlined multiple change points were identified based upon a penalty value of *23.79*. To force a single point to be detected the relevant penalty increased to 40.20 and restricted the change point to occurring between quarters 1 and 2 of 2014. The results presented above suggest rates of development on green space per 100,000 residential developments increased during the period defined by recession.

In contrast, the 'urban' subset was analogous with the overall '*Construction normalised*' data and distinguished a single change point after quarter 3 of 2013 [figure 4.14]. Significant differences were recorded between means, with the period after the change point reflecting an area of *132.94*, whereas the prior segment was *44.80*. Similarly notable deviation was reported in relation to the two variance statistics, logged as *3,327.30* after quarter 3 of 2014 and *458.84* before [table 4.13].

	Q1 2007 – Q4 2013	Q1 2014 - Q4 2018
Mean	44.80	132.94
Variance	458.84	3,327.30

Table 4.13: Urban Subset: Summary of '*Construction normalised green space loss*' mean and variance relating to the segments identified around the change point, based upon the optimal penalty value [57.61].

The relevant derived penalty value required to identify multiple change points was 11.95, whereas the single point discussed above was associated with a penalty of 57.61.

Through comparison between the raw and '*construction normalised*' data it is notable the '*construction normalisation*' removed the initial change point identified in regards to the 'urban' subset, but detected an additional one in the 'rural'. This can be interpreted as suggestive of distinct effects associated with economic circumstances in regards to each subset of the aggregated data.

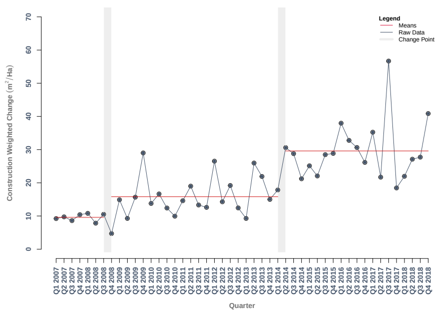

Figure 4.13: Graphical representation of Change Point Detection undertaken in regards to 'rural' Authority samples based upon '*Construction normalised*' change.

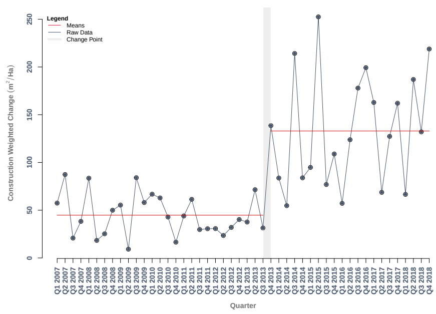

Figure 4.14: Graphical representation of Change Point Detection undertaken in regards to 'urban' Authority samples based upon '*Construction normalised*' change.

It is noted in regards to each data set, the occurrence of a structural change was identified at some point between quarters 3 of 2013 and 1 of 2014. With the periods after the change reflecting a mean area of green space subject to development, which was between *86.99%* (‘*Construction normalised*’ rural subset) and *309.52%* (raw ‘*green space loss ratio*’ urban subset) higher than the prior period.

4.4 Discussion

This research represents the first quantitative analysis to focus upon the developmental threat to green space that can be associated with the adoption of the *Localism Act 2011* and *National Planning Policy Framework*. In so doing it sought to apply novel methods as a means through which to explore the relationship between planing policy and green space.

For clarity, the research question which constitutes the aim of this study is reproduced:

Research Question 1: Has the area of green space which was subject to development evidenced alteration in rates which could be associated with the adoption of the *Localism Act 2011* and *National Planning Policy Framework (2012)*?

4.4.1 Key Findings

Initial exploratory comparisons of annual data segmented into pre-defined *pre-* (2007 to 2011) and *post-policy* (2012 to 2018) periods evidenced sufficiently different data profiles to suggest further analysis was needed. For example, mean values within the *post-policy* period were recorded as ***190%*** and ***142%*** higher than the corresponding *post-policy* periods.

Of particular note, the broadly bimodal distributions evidenced in the *post-policy* periods (2012 to 2018) suggested the existence of two distinct segments, which were considered to potentially reflect the persistence of the prior policy regime. By redefining the policy periods, in accordance with the 2 year estimate between approval and completion used in research by Shelter (2019), the data evidenced highly divergent profiles.

The outlined differences in both '*green space loss*' and '*construction normalised*' data evidenced the existence of a structural change having occurred in the data at some point during the research period. Whilst the redefinition of the *pre* and *post-policy* periods supported the existence of a lagged effect (Shelter, 2019), which had not been explicitly discussed in relevant research (Dallimer et al., 2011) and should be incorporated as an essential consideration in future analyses.

From the perspective of policy analysis it can be contended the summary methods utilised in this section of research do not reflect a robust measure of causal inference (McDowall and McCleary, 2014). However, they are analogous with elements of comparable studies, which reported *pre-test - posttest* results (Ganser and Williams, 2007; Kasraian et al., 2019; Mu et al., 2016). Furthermore, it was consistent with the approach described in Dallimer et al. (2011), which evidenced a reduction in the proportional green space coverage between 2001 and 2006. Considered in combination, Dallimer et al. (2011) and the results reported in this research advance a diminishing area of green space under two contrasting policy regimes between 2001 and 2018.

However, the extent to which this effect can be associated with the implementation of the *Localism Act 2011* and *National Planning Policy Framework* required additional analytical methods (Plieninger et al., 2016). Subsequent application of mean and variance based *change point detection* methods indicated the most likely point at which a change occurred in the process which generated said data. In regards to both data sets the same change point was identified as quarter 3 of 2013. However, it should be understood that due to the delay between change occurring and it being logged within the data this may include data related to quarter 1 of 2013 (Ordnance Survey, 2020).

The outlined results develop a clear picture of the rate of development upon green space having materially changed. However, the direct attribution of this effect to the revised policy agenda is more problematic in light of the complex socio-economic, geophysical, technological (Hersperger et al., 2018) and cultural (HOXHA et al., 2014) influences upon land use change, in conjunction with structural delays inherent to the planning process (Callcutt et al., 2007; Lichfields, 2016; Shelter, 2019).

Due to the pronounced, abrupt impact evident within the data an assumption was made the change was unlikely to have been caused by significant geo-physical, technological or cultural factors. The effects of such influences are considered likely to be more gradual (Hersperger et al., 2018) and therefore would not be anticipated to result in an easily discernible change point (Vogt et al., 2015).

Consequently, it was deemed reasonable to restrict consideration of the potential causes for the outlined change to a combination of socio-economic or policy features. Within the research period, the most feasible of which were identified as the amended policy, the economic crisis and subsequent recovery (Edmund et al., 2009; Department for Business, Innovation and Skills, 2013) or the increased pressure upon Local Authorities to sell land as a result of the austerity agenda (Neal et al., 2016; Locality, 2018).

Within the research, through analysis of '*construction normalised*' data, which reported the area of green space upon which development occurred per 100,000 residential construction projects, attempts were made to control for the influence of the economic crisis (Olga and Antonios, 2019). Critically, the same single change point was identified (quarter 3 of 2013), with a penalty value four times larger than the minimum at which multiple change points would be detected. Furthermore, when relevant penalty values were adjusted to allow for multiple change points to be detected both occurred between 2013 and 2014.

Provisionally, these results could be interpreted as precluding the economic crisis as the central reason for the change. However, this is predicated upon the validity of the data as a means by which to account for economic circumstance. Whilst the Department for Business, Innovation and Skills (2013) reported rates of non-residential development were unaffected between 2007 and 2010, rates of residential development were recognised as highly reflective of the recession and recovery.

Therefore, the area of green space upon which development occurred as a proportion of total development would be reduced in the years 2007 to 2010 when compared to residential only. Should the *post-policy* period have been marked by increased non-residential development as well, relative statistics might be considered an over-estimation. With no equivalent data relating to the period after 2012 it is difficult to establish the potential effect upon the data. However, the weighted economic value of non-residential construction in the years after 2012 was evidenced to have remained below levels recorded in 2007 and 2008 (ONS, 2018b), from which it can reasonably be conjectured rates of development would be unlikely to significantly skew the data.

Furthermore, analysis of GDP noted that despite nascent signs in 2013, the construction sector did not fully recover until 2015 (ONS, 2018a). Were the recorded increased rate of development on green space directly associated with such it would be anticipated a change point would only be detected during or after 2015.

Accordingly, the outcome of the '*construction normalised*' data was deemed likely to provide a reliable means through which to mitigate against economic drivers affecting the analysis (Olga and Antonios, 2019).

However, separate consideration must be afforded to the potential influence of the 'austerity' agenda upon land sales. Under pressure to generate revenue it has been reported that Local Authorities have increasingly relied upon the sale of publicly owned land (Locality, 2018). The value of said land is highly dependent upon planning rights (Catney and Henneberry, 2019), which may imply that to ensure adequate remuneration Local Authorities would allocate such as appropriate for development. Therefore, released land may be more likely to undergo development. Accessible land ownership information was incorporated into the research data (Ordnance Survey, 2016) to address the outlined issue, but analysis was unable to establish such for large amounts of identified land. Therefore, consideration is afforded to alternative relevant resources.

In reality public land sales have been dominated by existing built infrastructure, particularly where situated within existing urban cores (Shrubsole, 2019). In addition to which the extent of Local Authority land ownership Nationally represents around 4% of the total area (Shrubsole, 2019). Therefore, it could reasonably be inferred that the effect of this issue upon the outcome of the analysis would be minimal.

In view of research which suggests the time frame between planning approval and the completion of development can range from anywhere between 10 months (Lichfields, 2016) and 3.2 years (Callcutt et al., 2007), the seven quarter (21 month) interval between the introduction of the *NPPF* (representing the latest policy change) and identified change point appears consistent with attribution of the effect to such. It should additionally be born in mind the data can be considered to reflect the start of ground works for development and therefore should be subject to a reduced time interval.

Correspondingly, in the only UK based conceptually comparable research produced to date, the altered profile of land cover change data across the research period was deemed to constitute evidence of the impacts associated with planning policy (Dallimer et al., 2011). Said research was based upon cumulative *pre* and *post-policy* differences and as such did not empirically test for an attributable change point. However, in attempting to assess the impact of the policy which preceded that which was analysed in this research, both results considered collectively evidence an accelerating reduction of green space between 1991 and 2018. Dallimer et al. (2011) further presented a framework in which land cover was assumed to rapidly respond to policy effects, which is empirically corroborated by this research.

Although potentially considered as a reductive approach (Hersperger et al., 2018), there is a sufficiently robust research foundation which has established policy as the most influential reason for land use and land cover change (Salata et al., 2015; Wu et al., 2019). Therefore, it is argued there exists judicious evidence through which to suggest the detected change point could likely be significantly attributed to the policy change.

Based upon such, this research conceptually presented *change point detection* as a method through which to empirically test for the existence of policy effects using land change data. Having only previously been applied to satellite imagery (Ramachandra, 2019) as a means to detect an economic event through deforestation the expansion of the approach to include other drivers appears practicable. However, the evidential impact of economic factors upon the data suggests the need to consider relevant confounding influences (Hersperger et al., 2018).

This research further suggests vector based resources could support urban science in developing models of change at a highly granular spatial scale not achievable with most remote sensed imagery (Orford and Radcliffe, 2007). Although the validity of such requires the incorporation of complex revision processes (Ordnance Survey, 2020).

4.4.2 Strengths and Limitations

The strengths and limitations associated with this section of research are restricted solely to the analytical methodology. Wider issues related to data (such as the influence of land banking) and inferential validity are primarily discussed in **chapter** 7.

Change point detection is recognised as a strong method through which to identify material changes in time series data through mean and variance (Xu et al., 2015). Although more commonly applied to manufacturing quality control (Nair et al., 2000) or cyber security (Polunchenko et al., 2012) it has previously been utilised in regards to testing intervention effects (Friede et al., 2006). In Ramachandra (2019) *change point detection* was evidenced to successfully identify the occurrence of a significant economic event based upon the area undergoing deforestation. This study corroborates the capacity of this method to identify patterns in rates of land use change and suggests it could be deployed as a means through which to detect policy effects.

Where multiple change points were detected, the first in each instance coincided with a pre-identified economic event (Tatliyer, 2017). However, more substantial changes were identified as having occurred after the hypothesised transitional period.

Through accounting for changes in the profile of the data in a consistent period ranging from prior to and after the policy, the research is commensurable with equivalents (Dallimer et al., 2011). Whilst attempts to control for the most likely external influences upon analysis were undertaken, the relatively short *pre-policy* period may not accurately account for the developmental narrative under the previous policy regime.

Crucially the method does not appropriately account for prior trends and can therefore be considered more akin to *pretest - posttest* designs, which have been shown to be less inferentially robust than alternative policy impact assessments (such as *Interrupted Time Series* Analysis) (Cruz et al., 2017). Although this issue can to some extent be addressed through the use of both mean and variance as test statistics (Killick et al., 2012), as applied in this research.

A contention is also posited that change point detection methods are less reliable when applied to short time series (Cruz et al., 2017) and do not account for *auto-correlated* structures (Jarušková, 1997), which were present in the data. Furthermore, caution is recommended where standard methods, such as maximum likelihood approaches are used in relation to data with significant deviation from a normal distribution in the presence of outlying observations (Fearnhead and Rigaill, 2019).

However, the *PELT* algorithm utilised in this research has been evidenced to have performed reliably in relation to time series consisting of as few as 15 observations (van den Burg and Williams, 2020). Thus, the length of the time series is considered unlikely to invalidate the results. It is further contended cumulative mean and variance based methods reduce susceptibility to error associated with autocorrelation (Lund et al., 2007). Whilst the significance of the difference between the identified segments and testing for both single and multiple change points offer robust support for the validity of the results (Haynes et al., 2017).

Aminikhanghahi and Cook (2017) highlight the most prominent issue with *change point detection* methods as offering limited detail in regards to the effect or causes of change. However, as a primary indicator of the existence of change within core parameters they remain a useful research method (Killick et al., 2012) and have been utilised successfully in regards to environmental data, in the form of climate change (Gallagher et al., 2013) and hydrology (Chu et al., 2012). Whilst additionally proposed and tested as viable in regards to land use change (Ramachandra, 2019).

4.4.3 Implications

The outcome of this research is suggestive of national level policy representing a powerful regulatory instrument through which to influence patterns of land use and protect green space from development. This both supports and builds upon prior research, which reported national policy provisions as a significant underlying factor in land change (Dallimer et al., 2011; Ganser and Williams, 2007; Mu et al., 2016), offering empirical evidence supportive of a tacit assumption which underpins policy making (Garcia-Martin et al., 2020).

It suggests that minimal reductions in the protection explicitly provided to green space or the removal of targets for 'brownfield' development may dramatically alter the rate of development occurring on previously undeveloped land within relatively short time scales. Where Kasraian et al. (2019) evidenced regulatory policy to retain a long term residual effect, this research identified a significant change to the profile of development within a period of less than 2 years, implying policy change has the capcity to alter lanscapes more quickly than previously suggested. To date the relationship between policy and land change has assumed a long transitional period (Bengston et al., 2004; Kasraian et al., 2019; Morrison and Pearce, 2000; Mu et al., 2016), which is challenged by the outlined time frame.

One can speculate as to methodological causes of this disparity. Namely, the use of highly granular vector data, which enabled the identification of small scale land use change potentially less easily discerned in satellite equivalents (Horning and DuBroff, 2004). Additionally, it is the only research to provide a consistent data set based upon a quarterly time interval, facilitating a more rigorous, empirical determination of the point at which effects became evident. Contextual attributes must also be addressed, with the largely discretionary system operating within England evidenced to be highly responsive to policy effects (Dallimer et al., 2011), which may not be replicated within systems dominated by zoning (Booth, 1995).

However, the research should inform policy practice by offering new insights in regards to the time frames associated with the transition between policy instruments (Morrison and Pearce, 2000). From a UK perspective or nations adopting similar approaches, policy makers could consequently seek to develop evaluation instruments based upon a short time frame, which allow for potentially negative effects to be redressed quickly. Whilst future research can build upon this foundation and continue analysis of the policy effects using the outlined as a base line. However, it is important to further develop a conceptual understanding of the extent to which the impacts of policy reflect a place neutral approach (McGuinness and Mawson, 2017), whereby they are felt homogeneously across all land types or evidence differentiated effects upon distinct land types.

4.5 Conclusion

The vital importance of green space as a contributor to core ecosystem service functions means it is imperative to develop a clear understanding of its relationship with spatial planning policies, which represent the primary means of regulation (Hersperger et al., 2018). Increased rates of development upon such land can threaten habitats with total loss or fragmentation, reduce air quality, exacerbate flood risk, reduce the capacity to provide food and severely impact upon social well being.

Empirical analysis of the area of green space which was subject to development between 2007 and 2018 suggests the occurrence of a change point in quarter 3 of 2013, after which rates increased. Whilst difficult to establish with certainty, the research presents a sound evidential basis with which to add to the existing discussion related to the impacts attributable to the introduction of the revised planning framework, under the *Localism Act 2011* and *NPPF*.

Although it can be argued individual provisions may not reflect a fundamental change to previous policy, outlined results support the existence of an implicit diminution to the protections afforded to previously undeveloped land. Through association with a perceived pro-development tone, which resides at the core of the framework, the subsequent amendment published in 2018 might be considered unlikely to have reduced the developmental threat to the majority of green space. This highlights the need for reform of planning policy to be informed by *ex post facto* research, in order to ensure that detrimental impacts are identified and addressed within the policy cycle.

Through *change point detection* the existence of a policy effect can be identified, but provides no means through which to reliably understand the magnitude of such. Without which, the advancement of sustainable solutions become less likely.

CHAPTER 5

England Green and England Grey

Quantifying Policy Effects

"*And that will be England gone,*
The shadows, the meadows, the lanes,
The guildhalls, the carved choirs.
There'll be books; it will linger on,
In galleries; but all that remains,
For us will be concrete and tyres."

Going, going
Larkin (1972)

Incongruously nestled within the dense suburban environment of the London Borough of Ealing is situated a 2.8 Hectare [Ha] (Ealing Council, 2012) area of undeveloped, allotment land, which has resolutely endured through 188 years of relentlessly encroaching urbanisation (Watts, 2017). The vast, virescent tapestry of agricultural land within which the '*Ealing Dean Allotments*' site was once situated had been lost to housing development by the early 1800s (Bolton et al., 1982). However, the 8.3 Hectares (Ealing Dean Allotments Society, 2014) of common land enclosed as allotments under the provisions of the *Poor Relief Act 1832* (Bolton et al., 1982) remained largely undiminished until the 1970s (Watts, 2017).

By 2017, whilst the site had been reduced to under forty percent of its original land area (Ealing Council, 2012), it continued to provide 141 plots for the local community (Ealing Dean Allotments Society, 2017) and was bounded by hedgerow designated as a '*site of local importance for nature conservation*' (Ealing Council, 2008), through which it was recognised as being of value to wildlife and biodiversity (Greater London Authority, 2017).

Despite evidenced social (Howe and Wheeler, 1999) and natural value (Speak et al., 2015), in 2017 the '*Ealing Dean Allotments*' site was subject to an approved development proposal, which would reduce its area by a further ten percent (Pathways, 2016). Whilst the proposal was subsequently withdrawn, the developmental narrative of '*Ealing Dean*' can be considered to offer a simple illustration of the tension between the provision of housing and retention of green space, which resides at the heart of contemporary planning. Despite evidence of a shift in balance, which threatens 'natural' land with increased development [chapter 4], the effect associated with policy change has not been quantified.

5.1 Introduction

Balancing the needs of an expanding urban population (Budruk et al., 2009) against the environmental and social impacts associated with the loss of natural land constitutes a core element of sustainable development (Bruff and Wood, 2000) and subsequently a key concern for planning (Rydin, 1995). This concept has been enshrined within the European Union's political agenda through a commitment to '*no net land take*' by the year 2050 (European Commission, 2016). The role of policy is consequently theorised as a regulatory function through which to direct and constrain development. However, the empirical impact evaluation of this role has been limited.

In order for planning policy to meet varied objectives, such as the retention of undeveloped land to support sustainable development, it is considered essential that policy makers have *a posteriori* knowledge of the intended and unintended effects associated with different instruments (Alexander, 2016; Laurian et al., 2010). The development of evaluative procedure has been recognised as a research priority since the early 2000s (Morrison and Pearce, 2000), but remains unresolved to date (Shahab et al., 2019).

Single effect studies to explore the impact of particular policies upon patterns of development have been undertaken. For example, analyses of the efficacy of 'Green Belt' and equivalent regulatory policies (Bengston and Youn, 2006a; Elson et al., 1993; Kasraian et al., 2019) or the imposition of 'brownfield' development targets in contributing to the retention of undeveloped land (Baing, 2010; Dallimer et al., 2011; Ganser and Williams, 2007; Ganser, 2008).

However, the majority have struggled to apply methods to systematically discern the degree to which the identified effect can be attributed to the policy (Morrison and Pearce, 2000).

This '*attribution problem*' (Bovaird, 2014) is identified as being related to two factors (Morrison and Pearce, 2000). The first concerns the ability to isolate the effects from other driving forces (Hersperger et al., 2018; Morrison and Pearce, 2000). Whilst the second relates to the development of a reliable counterfactual scenario, representing the outcome that would have occurred without the policy (Morrison and Pearce, 2000; Shahab et al., 2019). Robust impact evaluation further requires a clear transition from one policy state to another (Morrison and Pearce, 2000) in conjunction with consistent and sufficient data relating to both periods (Vedung, 2017). This issue is commonly more difficult than assumed, particularly in relation to a set of national provisions, which is the reason most analyses focus upon specific provisions (Morrison and Pearce, 2000).

The transition to the *Localism Act 2011* and *National Planning Policy Framework* in England offered a contemporary subject of inquiry. Although much of the prior legislative framework remained in place (Winter et al., 2016), the reforms were considered to constitute a significant shift in developmental tone (Sibley-Esposito, 2014). Said reforms had also been identified as of significant interest in research related to the transition to the prior policy regime (Dallimer et al., 2011) and as a result provide an apposite continuum.

Chapter 4 identified a distinct change point in the rate of development upon green space and suggests the ability to distinguish the effect of policy through accounting for the predominant confounding effects (the economy and construction sector (Morrison and Pearce, 2000)). Therefore, this chapter expands upon the earlier work by applying a synthetic counterfactual approach (HM Treasury, 2020b) in order to evolve a quantitative policy effect.

5.1.1 Primary Research Aim

In **Chapter 4** analysis established that the area of green space subject to development underwent a statistically significant change after quarter 3 of 2013 of the data. A rationale was introduced whereby the most feasible cause of the identified change was the delayed effect associated with the introduction of a revised planning framework around 2012.

However, a key element in the evaluation of policy, thus influencing the means to inform future practice requires clear, quantifiable effects (Krizek et al., 2009; Crato and Paruolo, 2019). Historically, within the context of planning such evidence has been lacking (Shahab et al., 2019), as a result of which reform has been dominated by historical path dependency (Raco, 2014), acting as a restraint upon change (Haughton and Allmendinger, 2013), or reflects the cyclical nature of prevailing political ideology (Davoudi, 2011).

For example, governmental reform of national planning occurred in 2004, 2008 and 2011 (Davoudi, 2011), with negligible reference made to previous outcomes. There are a variety of reasons for a lack of integration between evidence and policy (Head, 2010), chief amongst which is the absence of sufficient quality data (Boaz and Ashby, 2003). This is a particular issue for the planning paradigm, which is often intended to achieve myriad outcomes (Hersperger et al., 2018), in regards to which access to reliable data is often limited (Bengston et al., 2004). Whilst, the complexity inherent to the interaction between the planning system and land use (Sengupta et al., 2016) requires robust analytical techniques (HM Treasury, 2020b).

Therefore, through the use of a robust quasi-experimental method, utilised in other policy analyses (Kontopantelis et al., 2015) this research is intended to address the following research question.

Research Question 2: What effect have the *Localism Act 2011* and *National Planning Policy Framework* had upon the total area of green space which has been subject to development?

5.1.2 Contribution

This research employs a previously unused approach to statistical analyses, which enabled the establishment of a quantified intervention effect deemed likely to be attributable to the adoption of the revised planning framework. Consequently, it can be considered to improve understanding of the dynamic relationship between changes to policy and urban induced green space land change.

In all prior research, which has sought to explore the effects associated with policy (Bengston et al., 2004; Dallimer et al., 2011; Kasraian et al., 2019; Mu et al., 2016), analytical methods have either used regression models (Dallimer et al., 2011; Kasraian et al., 2019) or simple *pretest-posttest* designs (Dallimer et al., 2011), considered less robust (particularly in relation to complex systems (HM Treasury, 2020b)) than methods which employ a counterfactual (McDowall et al., 2019). Although well established as a means of intervention analysis within the spheres of public health (Andersson et al., 2006; Ansari et al., 2003; Bloor et al., 2003; Bernal et al., 2017; Dowding et al., 2011; Murry et al., 1993; Penfold and Zhang, 2013; Serumaga et al., 2011), social welfare (Pridemore et al., 2007, 2013), criminal justice (Britt et al., 1996; Lane and Hall, 2019; Ramirez and Crano, 2003; Humphreys et al., 2017) and economic policy (Bonham et al., 1992; Campbell and Allen, 2001; King-Meadows and Lowery, 1996), the adopted methodology has not previously been applied within the context of planning.

Methodologically, the research tests the potential use of *Interrupted Time Series* Analysis to support inferential analysis of planning policy and provides a basis upon which comparable methods could be applied in other contexts. Additionally, it augments a limited field of research in which *Interrupted Time Series* Analysis is modelled using State-Space principles (Brodersen et al., 2015), which can account for non-stationarity and uncertainty (Fei et al., 2011). It further expands the application of the conceptual algorithm proposed by Ramachandra (2019) as an approach to interpret the impact of interventions upon land change.

5.1.3 Chapter Structure

Relevant sections within this chapter respectively outline; a brief description of the method upon which analysis is founded [section 5.2]; derived results [section 5.3]; a discussion framed around the related research that has informed said approach [section 5.4]; and a conclusion, which includes implications for policy practice [section 5.5].

5.2 Methods

To address the outlined research question an *Interrupted Time Series* analysis approach was employed. The use of this method has become well established within commensurable policy contexts (Britt et al., 1996; Bernal et al., 2017) and has been adopted recently in regards to the interpretation of land change effects (Ramachandra, 2019). The method reflects a computational systems modelling approach through which to derive a synthesised model of the state of interest in the absence of the policy, which can be compared with the real outcomes (HM Treasury, 2020b).

My approach to implement this method applied two distinct models, in the form of standard segmented regression (Bernal et al., 2017; Lane and Hall, 2019) and an alternative Bayesian forecast model (Brodersen et al., 2015). With the following steps undertaken and discussed in the subsequent sections:

1. Definition of variables used in the research;
2. Temporal range and segmentation around policy implementation;
3. Pre-analytical tests for the presence of *seasonality* and *auto-correlation*;
4. Analysis of intervention effects based upon segmented regression methodology;
    i. Selection of an appropriate model through comparison of alternative structures using AIC values;
    ii. Application of the final model to the complete time series;
    iii. Prediction of a synthesised '*counterfactual*' for the relevant *post-policy* period;
    iv. Derive the intervention effect based upon the relevant regression model;
5. Analysis of intervention effects based upon forecast model methodology;
    i. Derive variance estimates for *dynamic linear model* parameters;
    ii. Conduct functional test of fit against comparable *OLS*, *GLM* and *ARIMA* models using *MAE* and *RMSE*;
    iii. Application of best fitting model [*dlm*] to the defined *pre-policy* period;
    iv. Forecast a counterfactual scenario through the extrapolation of *pre-policy* trend;
    v. Application of *dlm* to *post-policy* period to model the trend;

vi. Derive an intervention effect based upon the absolute difference between the counterfactual prediction and modelled *post-policy* values;

5.2.1 Research Data

Green Space Loss Ratio

The '*green space loss ratio*' data used in this research was primarily obtained from *OS Mastermap*® topography layer data (Ordnance Survey, 2017), supplemented by *AddressBase Premium*® classification criteria (Ordnance Survey, 2018a).

OS Mastermap® topography layer is a digital, geospatial, vector data resource, which represents the majority of UK landscape features (including built forms and natural features) (Orford and Radcliffe, 2007). It is both highly detailed and accurate (Smith et al., 2007), with three tiers of classification criteria (Ordnance Survey, 2017). Whilst, previous iterations of identical geographic areas can be accessed in archival form from 2007 (Ordnance Survey, 2018b).

OS *AddressBase Premium*® is a geo-referenced record of contemporary and historic features, for which a postal address has been recorded (Ordnance Survey, 2018a). Relevant records also include building classification criteria and dates of entry or deletion.

'*Green space loss*' was derived through a 'minimum change' methodology (outlined in detail in **Appendix A**), which ostensibly used relevant *OS Mastermap*® '*make*' and '*descriptive group*' classifiers to identify the area of land which underwent transition from 'natural' form to 'built' environment (including the start of ground works preceding complete development) between time intervals. To ensure validity, a change was only included within the data where it could be verified against an appropriate *AddressBase Premium*® record.

The final data set therefore, represents the aggregate area of green space, which was subject to development during each quarter, as a proportion of the available green space area at that time (hereafter referred to as the '*green space loss ratio*').

Figure 5.1: Source: Ordnance Survey (2018b)
An example of the 'green space loss' data identified using the 'minimum change' method.

Construction Normalised Green Space Loss

In addition to the '*green space loss ratio*' data, a separate '*construction normalised*' measure was used in order to control for economic drivers of land use change. This data represented the aggregate area of green space loss per 100,000 residential developments begun within each quarter.

5.2.2 Temporal Range and Segmentation

Both data sets reflect univariate time series, comprising 48 quarterly observations, accounting for quarters 1 of 2007 to 4 of 2018.

Where referred to mathematically within the text the entire temporal range is represented as $t_0, t_{+1}, t_{+2}, t_{+3}...t_{+47}$, where t_0 is quarter 1 of 2007.

For the purpose of subsequent *Interrupted Time Series* analyses the data was segmented into periods in line with the intervention under consideration (Lane and Hall, 2019). The periodisation of the data was complicated by the existence of a 6 month delay in regards to data generation (Ordnance Survey, 2020), allied with an estimated period between the approval and completion of development ranging from 10 months (Lichfields, 2016) to 3.2 years (Callcutt et al., 2007). With the data underlying this research incorporating the period between approval and the beginning of preparatory developmental works, a two-year estimated lag was applied (Shelter, 2019). This was also supported by the prior analysis undertaken in **chapter 4**, (which suggested the existence of a change point between quarter 3 of 2013 and 1 of 2014) in accordance with the conceptual method outlined by Ramachandra (2019).

Therefore, the data was segmented into defined *pre-policy* (Q1 2007 to Q4 2011), *transitional* (Q1 2012 to Q4 2013) and *post-policy* (Q1 2014 to Q4 2018) periods. Two 'dummy' intervention identifier variables were coded into the data. The first, as '0' for quarters 1 of 2007 to 4 of 2011 (*pre-policy*) and '1' in regards to quarters 1 of 2012 to 4 of 2018 (*transitional* and *post-policy*). Whilst in the second, quarters 1 of 2007 to 4 of 2013 (*pre-policy* and *transitional*) were coded as '0', with quarters 1 of 2014 to 4 of 2018 coded as '1' [table 5.1].

	Intervention Code	Lagged Intervention Code
Pre-policy (Q1 2007 - Q4 2011)	0	0
Transitional (Q1 2012 - Q4 2013)	1	0
Post-policy (Q1 2014 - Q4 2018)	1	1

Table 5.1: Structural example of 'dummy' intervention identification variables. Each period can be identified based upon the values of both columns.

5.2.3 Pre-analytical Data Examination

Whilst pre-analytical tests utilising the *seastest* package in *R* (Ollech, 2019), excluded the existence of a seasonal effect upon the data, the *Durbin-Watson* test (Tillman, 1975) confirmed a significant positive auto-correlated structure (statistic reported *1.4357* and p-value *0.0152*).

This informed subsequent model choice, with *generalized least squares* [*GLS*] regression and *dynamic linear models* adopted, which could account for such structures within the data (Huitema and Mckean, 2000).

5.2.4 Segmented Regression

In adherence to standard approaches to *segmented regression*, the key variables (‘*green space loss ratio*’ and ‘*construction normalised change*’) were retained and analysed as single datasets, with segments identified through ‘dummy’ variables (Bernal et al., 2017).

In addition to the intervention identification variables discussed in **section 5.2.2**, ‘trend’ and ‘time’ variables were appended to the data. The ‘trend’ variable was coded as ‘0’ for each *pre-policy* period observation and a single increment increasing integer (1 to 28) in regards to *transitional* and *post-policy* observations. The ‘time’ variable consisted of numbers 1 to 48 across the entire time period [table 5.2].

	Intervention Code	Lagged Intervention Code	Trend	Time
Pre-policy (Q1 2007 - Q4 2011)	0	0	0	1:20
Transitional (Q1 2012 - Q4 2013)	1	0	1:8	21:28
Post-policy (Q1 2014 - Q4 2018)	1	1	9:28	29:48

Table 5.2: Structural example of ‘dummy’ trend and time variables.

For the purpose of regression analysis, the data was log transformed in order to both ensure an approximately normal distribution (Beard et al., 2019) and enable the recorded intervention effect to be reported as a simple percentage change (Lane and Hall, 2019). Relevant correlograms (limited to a maximum lag of 12) for auto-correlation and partial auto-correlation were utilised as a means by which to identify viable *autoregressive-moving average* [*ARMA*] terms [figures 5.2 and 5.3]. Consequently, a variety of viable *GLS* model variants were tested against the data, with different ARMA functions (Lane and Hall, 2019).

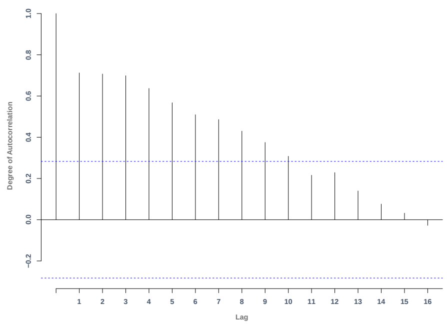

Figure 5.2: Plot of autocorrelation (log transformed quartered subset)

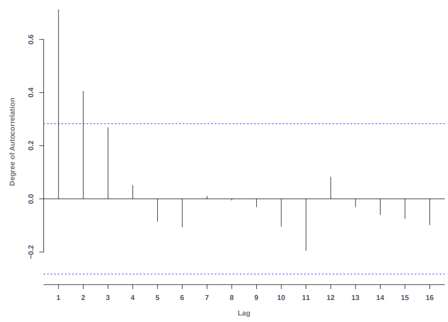

Figure 5.3: Plot of partial autocorrelation (log transformed quartered subset)

Based upon AIC values the most appropriate regression model in regards to both the '*green space loss ratio*' and '*construction normalised*' data included first order autoregressive (p) and moving average (q) ARMA terms.

The identified model was fit to the log transformed data, with the intervention effect subsequently derived from the changes in both level and trend between the *pre-policy*, *transitional* and *post-policy* periods [equation 5.1].

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 + \beta_3 + \beta_4 X_t \tag{5.1}$$

In the above equation (based upon Wagner et al. (2002); Lopez Bernal et al. (2018); Hudson et al. (2019)), Y_t is the estimated intervention effect at quarter t; β_0 constitutes the modelled baseline level (the *pre-policy* intercept); β_1 can be considered to represent the rate of change in area between each quarter of the *pre-policy* period (the *pre-policy* trend); T denotes the '*Time*' identifier (relating to quarters); β_2 corresponds to the level change which occurs between the *pre-policy* and transitional periods; β_3 the level change between the transitional and *post-policy* periods; β_4 represents the difference between the rate of change in area in the *post-policy* period when compared to the *pre-policy* equivalent (the change in trend); and X designates the '*Trend*' dummy variable.

Data was processed and modelled using *dplyr* (Wickham et al., 2015) and *nlme* (Pinheiro et al., 2007) packages in *R* (R Core Team, 2019), with relevant code reproduced in **Appendix C.1**.

5.2.5 Forecast Model

In the second distinct method to *Interrupted Time Series Analysis* a forecast model approach was utilised (Linden, 2018), based upon *dynamic linear models* (Bayesian State-space models) (Brodersen et al., 2015).

A *dynamic linear model* allows for the variation of parameters over time (Laine, 2020) and comprises observation and evolution equations (Petris and An, 2010) [equations 5.2 and 5.3].

$$y_t = F_t\theta_t + v_t, \qquad v_t\ N(0, V_t) \tag{5.2}$$

$$\theta_t = G_t\theta_{t-1} + w_t, \qquad w_t\ N(0, w_t) \tag{5.3}$$

The observation equation, y_t represents the product of the area of '*green space loss*', in the form of F_t and the state equation, θ_t, to which a mean zero error is added, v_t. Whilst G_t is the evolution vector, in this instance a 1 by 1 matrix representing time and w_t the underlying state errors assumed to have a mean of zero.

Firstly, relevant *pre-policy* period model variances were identified using maximum likelihood functions (Petris and An, 2010). Derived values in regards to '*green space loss ratio*' data were *0.013* for the observed variance (*v*) and *0.002* in regards to the underlying state (*w*). Whilst for the *construction normalised* equivalent *v* was *8.81* and *w* was less than *0.001*.

Applying the derived variance values, a first order polynomial *dynamic linear model* (evolving mean) was fit to the *pre-policy* data (Q1 2007 to Q 4 2011) based upon a *Kalman filter* algorithm (Petris and Petrone, 2011).

Following this step, the outlined models were assessed for fit against functional alternatives. In regards to the discussed *ARIMA* models, in each instance the most appropriate was identified (using *auto.arima* functions in *R* (Hyndman et al., 2007)) as a zero mean model (0,0,0), most likely as a result of insufficient data.

Both *MAE* and *RMSE* comparisons evidenced the respective *dynamic linear models* to out perform the estimation of the observed data derived from each of the other models [table 5.3]. Therefore, subsequent analyses were undertaken using the first order polynomial *dynamic linear model* outlined previously.

Model	*Mean Absolute Error (MAE)*	*Root Mean Squared Error (RMSE)*
Quartered *'Green Space Loss'*		
Ordinary Least Squares	0.08	0.12
Generalized Linear Model	0.08	0.12
ARIMA (0,0,0)	0.09	0.14
Dynamic Linear Model	**0.07**	**0.09**
Quartered *'Construction normalised'*		
Ordinary Least Squares	2.50	2.86
Generalized Linear Model	2.50	2.86
ARIMA (0,0,0)	2.48	2.89
Dynamic Linear Model	**2.23**	**2.70**

Table 5.3: MAE and RMSE comparison of prospective quartered pre-policy models (OLS, GLM, ARIMA and DLM)

The *dlmForecast* function (Petris and Petrone, 2011) was applied to the data with a 95% prediction interval based upon variance values. Initially a viable range of future mean states were estimated for each of the four observations within the first transitional year (2012), in which it was considered unlikely policy effects would be evident, based upon both the OS revision policy (Ordnance Survey, 2020) and relevant case law (DCLG, 2012b).

There was insufficient data with which to formally validate the models against available out-of-sample observations (Hansen and Timmermann, 2012). Representative of a common issue in policy analysis, where dependent upon real world data (Gertler et al., 2016). However, said prediction interval could be assessed against the small number of true observations. In regards to each observation for quarters 1 to 4 of 2012 the true value was within the range of the prediction interval [figures 5.4 and 5.5]. Accordingly, forecasts based upon such were deemed appropriate to act as a counterfactual, offering a robust approximation of '*green space loss*' under the continuation of the previous policy.

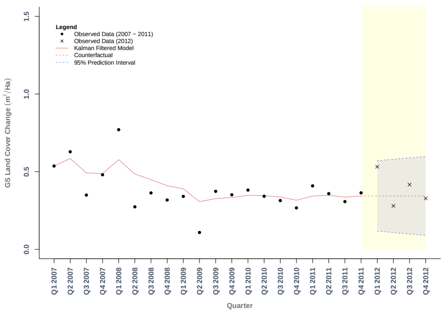

Figure 5.4: Graphical representation of counterfactual fit with out-of-sample future observation - '*green space loss ratio*' data

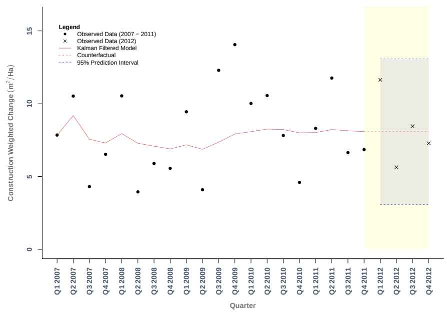

Figure 5.5: Graphical representation of counterfactual fit with out-of-sample future observation - 'Construction normalised change' data

Subsequently, the *post-policy* periods (Q1 2014 to Q4 2018) for each data set were modelled using the same approach outlined above. They reflected higher observed and state variances in their initial construction than the *pre-policy* equivalents. Relevant variance values were recorded as *0.153* (v) and *0.004* (w) in relation to '*green space loss ratio*', allied to *34.281* (v) and *0.500* (w) in regards to '*construction normalised change*'. Both can be considered to reflect the distinct data profiles across the two periods suggested by *change point detection*.

	Pre-Policy	Post-Policy
'Green Space Loss'		
Mean Absolute Error (MAE)	0.07	0.09
Root Squared Mean Error (RMSE)	0.93	0.76
'Construction normalised'		
Mean Absolute Error (MAE)	2.23	10.97
Root Squared Mean Error (RMSE)	2.70	11.56

Table 5.4: Comparison of *MAE* and *RMSE* values associated with *pre-* and *post-policy* periods.

Comparison of relative *Mean Absolute Error* and *Root Mean Squared Error* statistics showed the *post-policy* models evidenced significantly larger error statistics than in the *pre-policy* equivalents, primarily as a result of the existence of greater variance.

The intervention effect for each quarter during the *post-policy* period was calculated as the absolute difference between the maximum value associated with the counterfactual prediction interval and the modelled *post-policy* equivalent [equation 5.4].

$$\hat{IE}_{\tau} = \hat{y}_{\tau}^{post} - \hat{y}_{\tau}^{pre} \qquad \text{for} \quad \tau = t_{+28} ... t_{+47} \tag{5.4}$$

Where $\hat{IE}$ is the estimated minimum intervention effect, $\hat{y}_{\tau}^{post}$ the modelled *post-policy* value and $\hat{y}^{pre}$ the maximal predicted counterfactual value, based upon the continuation of the *pre-policy* model.

A cumulative intervention effect based upon the entire *post-policy* period was then calculated as the mean of the individual effects relating to $t_{+28}...t_{+47}$.

5.3 Results

5.3.1 Segmented Regression

Within this section results are initially presented in relation to the '*green space loss ratio*' dataset, before subsequent analysis of the '*construction normalised*' equivalent. All analysis reflects the log transformed data and as such can be considered to estimate level and trend change intervention effects as log differences, which are considered to equate to a percentage equivalent (Lane and Hall, 2019).

	Coefficient	*(95% CI)*	Standard Error	*P-value*
Baseline Intercept (β_0)	-0.840	(-0.982 to -0.698)	0.086	<0.001
Pre-Policy Trend (β_1)	-0.021	(-0.034 to -0.008)	0.008	0.010
Level Change in Transitional Period (β_2)	0.287	(0.089 to 0.485)	0.120	0.021
Level Change in Post-Policy Period (β_3)	0.744	(0.488 to 0.999)	0.155	<0.001
Trend Change in Post-Policy Period (β_4)	0.041	(0.023 to 0.060)	0.011	<0.001

Table 5.5: Intervention Effect model parameter estimates (with 95% Confidence Intervals), standard errors and *P-values* estimating log transformed area of green space which was subject to development.

Overall, the Intervention Effect model estimated that the area of green space subject to development increased by *28.72%* (*P = 0.022*) during the transitional period. Followed by a further *74.36%* (*P <0.001*) in the *post-policy* period. During the *pre-policy* period the area undergoing change each quarter was evidenced to have declined by *2.10%* (*P = 0.010*). However, after the implementation of the revised policy framework (excluding the transitional period) this trend had reversed, showing a *2.04%* increase per quarter, reflecting a total change in trend of *4.14%* (*P <0.001*) per quarter [table 5.5].

From the outlined results it was notable that there was evidence of a level change between the *pre-policy* and transitional periods, reflecting an increased area of green space upon which development occurred.

However, the significant level (*74.36%*) and slope (*4.14%*) changes reflected in the *post-policy* period can be considered to be broadly supportive of a structural change having occurred between 2012 and 2014. Said analysis shows that the area undergoing development in the *post-policy* period exceeded the *pre-policy* equivalent and markedly reversed the evident quarterly decline. These effects combine to cause an appreciable divergence between the *post-policy* period and synthesised counterfactual.

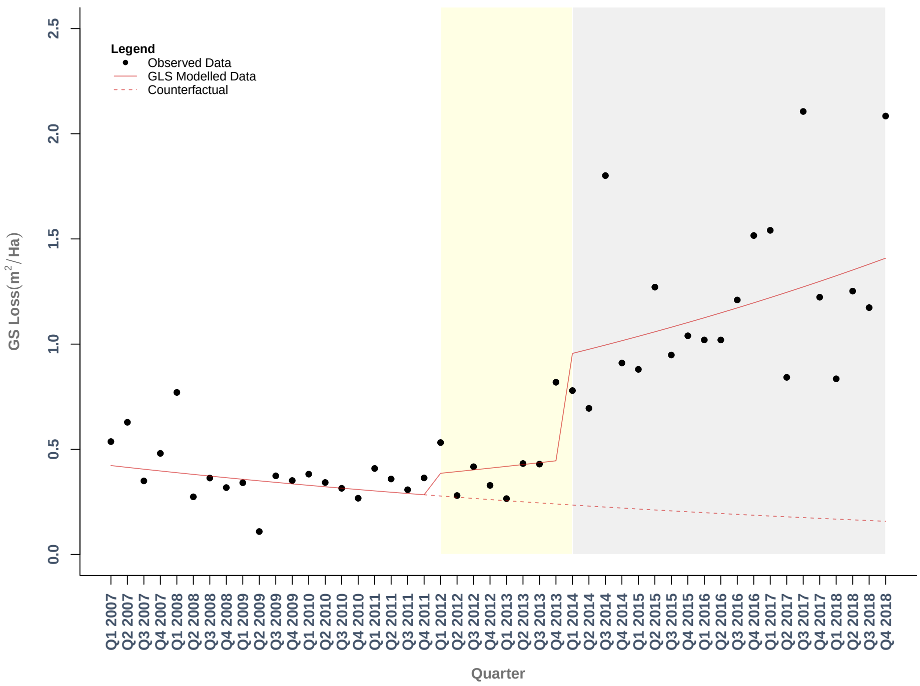

Figure 5.6: GLS Modelled ITS analysis of '*green space loss ratio*' data

It appears plausible that this effect could be attributed to the introduction of the revised planning framework. However, it can be contended that such fundamentally disregards the potentially confounding effect of the 2008 to 2009 recession (Edmund et al., 2009; Marrs, 2019) upon the *pre-policy* period. This is particularly pertinent in regards to the declining trend reported for the *pre-policy* period, which appears to have been heavily influenced by pre-recession quarters.

Therefore, it was imperative that data which sought to control for the potential effects of the recession were also analysed. Results relating to the '*construction normalised*' data should be understood to reflect the area of green space, which underwent development (m^2/Ha) per 100 thousand residential development projects where ground works began in the same time period.

	Coefficient	*(95% CI)*	Standard Error	*P-value*
Baseline Intercept (β_0)	1.860	(1.743 to 1.976)	0.710	<0.001
Pre-Policy Trend (β_1)	0.015	(-0.005 to 0.026)	0.006	0.019
Level Change in Transitional Period (β_2)	-0.058	(-0.217 to 0.102)	0.097	0.554
Level Change in Post-Policy Period (β_3)	0.691	(0.481 to 0.902)	0.128	0.001
Trend Change in Post-Policy Period (β_4)	-0.004	(-0.019 to 0.011)	0.001	0.688

Table 5.6: Intervention Effect model parameter estimates (with 95% Confidence Intervals), standard errors and *P-values* related to log transformed '*construction normalised*' data.

A level change equating to a *5.79 %* (*P = 0.554*) decrease in area was reported between the *pre-policy* and transitional periods, suggestive of the policy having negligible effect during the first eight quarters. However, the results estimated that within the *post-policy* period the area of green space undergoing transition to developed form was *69.15%* (*P <0.001*) higher than would have been anticipated under the previous policy framework. There was a negligible change identified between the trends in the *pre-* and *post-policy* periods, of -*0.371 %* (*P = 0.688*) per quarter [table 5.6].

Crucially, it should be noted that a significant level change remained between the *pre-* and *post-policy* periods, suggesting that the area of development to take place on green space was *69.15 %* greater than would have been anticipated under the continuation of the previous framework. It is also worthy of note that the gradually increasing trend (*1.54 %*) evidenced in the *pre-policy* period changed minimally (<*1 %* per quarter) after the adoption of the revised framework. This effect may indicate the '*construction normalised*' data suitably accounts for the underlying features which can be considered to contribute to rates of development.

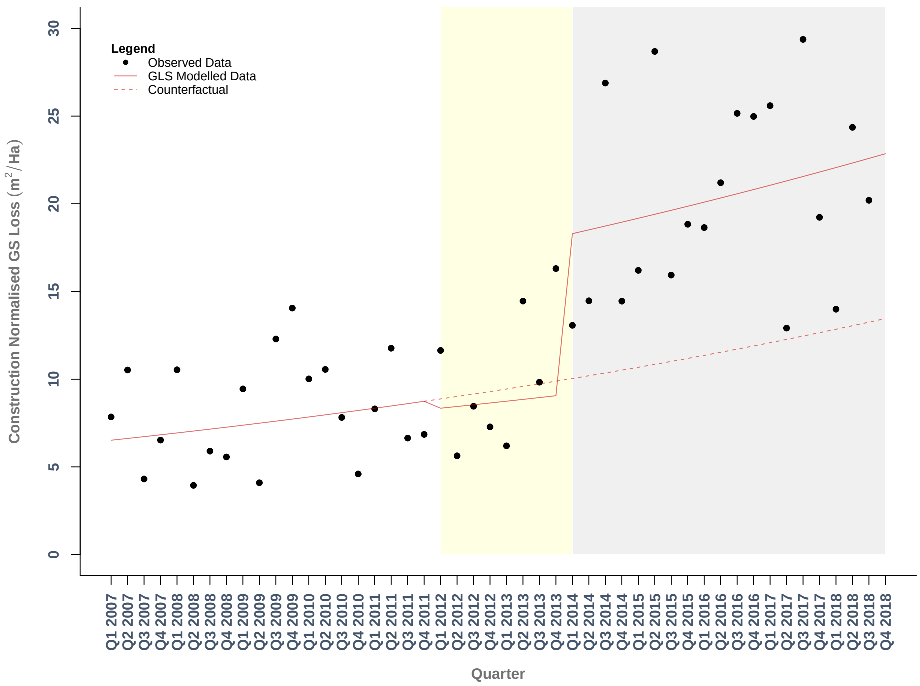

Figure 5.7: GLS Modelled ITS analysis of '*construction normalised green space loss*' data.

5.3.2 Forecast Model

It is reiterated that throughout this section the primary recorded results reflect an estimated,'minimum intervention effect' based upon the absolute difference between the modelled data relating to the *post-policy* period and the upper threshold of the corresponding synthesised counterfactual, based upon a 95% prediction interval. Brief comparison is made with results pertaining to the observed *post-policy* data in order to inform inference.

Results derived from the raw '*green space loss ratio*' data set are reproduced in **table** 5.7. On average, the area of green space land identified as having been subject to development in the *post-policy* period exceeded that which would have been predicted under the previous policy framework by ***56.54%*** per quarter based upon the mean intervention effect.

Year	Absolute Difference Modelled Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)	Absolute Difference Observed Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)
Q1 2014	**0.14**	***22.04%***	0.14	*22.04%*
Q2 2014	**0.09**	***14.01%***	0.05	*7.56%*
Q3 2014	**0.45**	***69.46%***	1.15	*175.83%*
Q4 2014	**0.39**	***59.55%***	0.25	*37.91%*
Q1 2015	**0.35**	***51.93%***	0.21	*31.93%*
Q2 2015	**0.39**	***58.22%***	0.60	*88.64%*
Q3 2015	**0.36**	***53.43%***	0.27	*39.38%*
Q4 2015	**0.36**	***51.88%***	0.35	*51.38%*
Q1 2016	**0.35**	***49.92%***	0.33	*47.14%*
Q2 2016	**0.34**	***48.13%***	0.32	*45.81%*
Q3 2016	**0.36**	***50.78%***	0.50	*71.50%*
Q4 2016	**0.42**	***59.48%***	0.80	*113.08%*
Q1 2017	**0.48**	***66.94%***	0.82	*114.76%*
Q2 2017	**0.42**	***58.03%***	0.12	*16.40%*
Q3 2017	**0.56**	***76.96%***	1.38	*188.85%*
Q4 2017	**0.55**	***74.20%***	0.49	*66.44%*
Q1 2018	**0.47**	***63.78%***	0.09	*12.80%*
Q2 2018	**0.47**	***63.37%***	0.51	*67.86%*
Q3 2018	**0.46**	***61.28%***	0.42	*56.19%*
Q4 2018	**0.59**	***77.52%***	1.33	*175.46%*

Table 5.7: Estimated Intervention effect derived from quartered '*green space loss*' data. Results based upon the primary metric are highlighted in bold.

Based upon the counterfactual scenario it was anticipated that development would have occurred on a maximum **0.70m^2/Ha** of green space per quarter. However, the modelled *post-policy* period recorded the actual area which underwent change from green space to developed form to be **1.10m^2/Ha** per quarter, thus suggesting that an additional **0.40m^2/Ha** was lost to development in each quarter since the implementation of the revised framework.

This can be considered to translate to an average area of **68.62 Ha** per quarter (around 96 football pitches) and a cumulative area of **1,372.33 Ha** (0.8% the size of London) across the entire *post-policy* period.

Positive intervention effects were recorded in regards to each quarter of the *post-policy* period, representing evidence of additional green space land being lost to development, where measured against the absence of the policy change. The smallest effect estimated a *14.01%* (**0.09m^2/Ha**) increase in quarter 2 of 2014. Whilst, it was estimated development occurred on an area *77.52%* (**0.59m^2/Ha**) greater than anticipated in quarter 4 of 2018, representing the largest single quarter intervention effect.

The general trend modelled in the *post-policy* period evidenced an increasing area of green space land being lost per quarter, at an average rate of around **0.02m^2/Ha**. During the first ten quarters under the revised policy framework the average intervention effect recorded a *47.68%* increase in the area on which development occurred. Whereas, between quarter 3 of 2016 and quarter 4 of 2018 it had risen to *65.23%* and contained 7 of the 10 largest recorded single quarter intervention effects. Such can be considered to suggest the intervention may have caused a sustained and increasing effect upon green space development (Bernal et al., 2017) [figure 5.8].

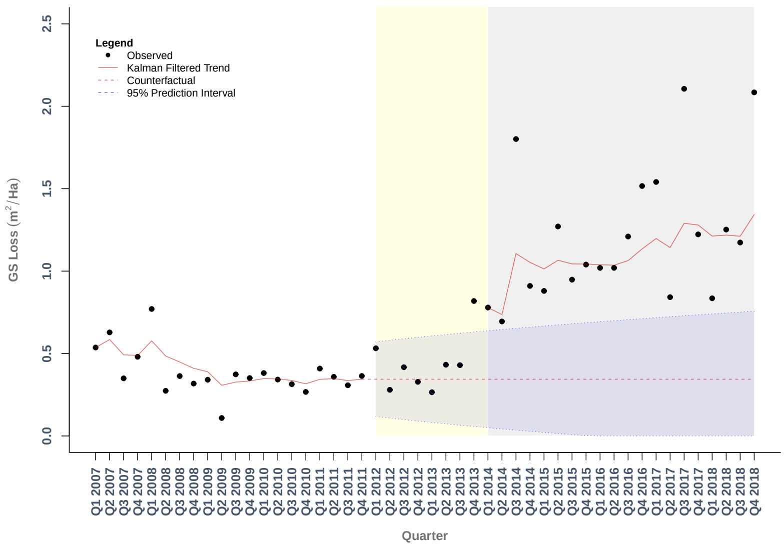

Figure 5.8: Graphical representation of quartered subset DLM ITS Analysis

Results derived separately based upon the difference between the *post-policy* observations and counterfactual boundary were significantly different, with a per quarter average effect estimated as *71.55%*. The disparity between the two statistics can be attributed to the large variance in regards to the observed data and the influence of outliers upon the results, such as the large effects associated with quarters 3 of 2014, 4 of 2016, 1 and 3 of 2017, and 4 of 2018.

However, the observed data relating to individual quarters may be subject to anomalies, which could distort results. Therefore, the use of the underlying trend can contribute to more reliable inference.

From the outlined results, across the entire *post-policy* period the inferred intervention effects suggest the area of green space subject to development exceeded the predicted rate assumed under the previous regime by an average of ***56.54%***.

However, the attribution of this effect to the provisions within the *Localism Act 2011* and *NPPF* can be cast in doubt, particularly in light of the concurrence with a seismic economic event in the form of the recession of 2008 to 2009 and subsequent recovery.

Where data reflected the area of green space upon which development occurred per 100,000 residential developments, results continued to suggest a significant intervention effect [refer to **table 4.5**]. It was estimated each quarter saw a mean average green space area ***45.59%*** larger than predicted under the previous policy framework subjected to development. Where the median was applied as an alternative the intervention effect rose to ***49.27%***.

An average difference of **5.97m^2/Ha** (per 100k development projects) was recorded, based upon the **13.08m^2/Ha** (per 100k development projects) predicted based upon the counterfactual and **19.05m^2/Ha** (per 100k development projects) modelled upon the same period subject to the revised framework.

Therefore, for every 100,000 residential developments an average additional area of green space equating to ***1,023.36 Ha*** per quarter (around 1,433 football pitches) was lost since the adoption of the *Localism Act 2011* and *NPPF*. Accordingly, throughout the *post-policy* period a total green space area of **203,571.80 Ha** (1.29 times the size of London) which would not have been predicted to be subject to development was built upon.

In the modelled *post-policy* period, after quarter 1 of 2014, in which no intervention effect was estimated, the area of green space undergoing change subsequently remained above the maximal predicted counterfactual. The estimated intervention effect ranged from *5.31%* in regards to quarter 2 of 2014 to *68.07%* in quarter 4 of 2018, with an underlying trend which reported an average *3.58%* increase per quarter.

Between quarter 1 of 2014 and quarter 2 of 2016 the average area of green space which underwent development was *32.75%* greater than under a null effect scenario. During the second half of the *post-policy* period (quarter 3 of 2016 to quarter 4 of 2018) the area was *58.43%* higher, supporting the existence of an increasing effect.

Interestingly, based upon the difference between the observed data and counterfactual the average intervention effect (*59.32%*) was relatively similar to that which was recorded by the modelled raw *post-policy* data (*56.54%*). This may imply the *dynamic linear model* suitably accounted for the underlying economic influence (Laine, 2020).

Year	Absolute Difference Modelled Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)	Absolute Difference Observed Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)
Q1 2014	**0.00**	***0.00%***	0.00	**0.00%**
Q2 2014	**0.69**	***5.31%***	1.39	**10.62%**
Q3 2014	**5.17**	***39.50%***	13.80	**105.49%**
Q4 2014	**4.17**	***31.87%***	1.37	**10.44%**
Q1 2015	**3.94**	***30.14%***	3.12	**23.86%**
Q2 2015	**6.14**	***46.90%***	15.6	**119.28%**
Q3 2015	**5.58**	***42.67%***	2.85	**21.81%**
Q4 2015	**5.61**	***42.87%***	5.75	**43.97%**
Q1 2016	**5.6**	***42.82%***	5.56	**42.52%**
Q2 2016	**5.95**	***45.46%***	8.12	**62.06%**
Q3 2016	**6.76**	***51.64%***	12.07	**92.28%**
Q4 2016	**7.41**	***56.67%***	11.90	**90.93%**
Q1 2017	**8.05**	***61.53%***	12.51	**95.65%**
Q2 2017	**7.04**	***53.85%***	0.00	**0.00%**
Q3 2017	**8.16**	***62.36%***	16.29	**124.52%**
Q4 2017	**7.92**	***60.53%***	6.15	**46.98%**
Q1 2018	**7.09**	***54.21%***	0.91	**6.92%**
Q2 2018	**7.58**	***57.95%***	11.28	**86.20%**
Q3 2018	**7.53**	***57.54%***	7.12	**54.39%**
Q4 2018	**8.90**	***68.07%***	19.43	**148.56%**

Table 5.8: Estimated Intervention effect derived from quartered '*Construction normalised green space loss*' data. Results based upon the primary metric are highlighted in bold.

The '*Construction normalised green space loss*' data evidenced a continuing, significant difference between the *post-policy* observations and counterfactual predictions, suggestive of a long term intervention effect potentially associated with the revised planning policy framework. The area of green space land upon which development occurred was assessed as ***45.59%*** higher under the new framework than was modelled based upon the continuation of the previous planning policy [figure 5.9].

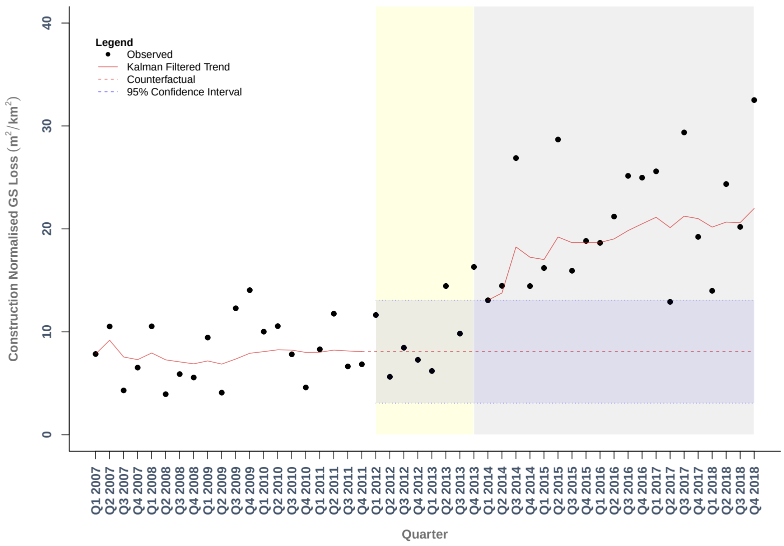

Figure 5.9: Graphical representation of 'Construction normalised' quartered subset DLM ITS Analysis

5.4 Discussion

The research presented within this chapter sought to empirically investigate the impact upon the prevalence of green space associated with the adoption of different approaches to National Planning Policy within the context of a single country. To address this research gap the outlined core question was investigated.

Research Question 2: What effect have the *Localism Act 2011* and *National Planning Policy Framework* had upon the area of green space which has been subject to development?

5.4.1 Key Findings

By applying an established quasi-experimental method, which is recognised as offering robust inferential analysis of impacts associated with interventions (Fretheim et al., 2013), this research estimated the effect of a change to national planning policy upon rates of development on green space land. Derived results indicate a significantly larger area of green space was subject to development in the defined *post-policy* period than would have been predicted based upon the continuation of *pre-policy* trends.

The consistent level changes presented by *segmented regression* (69% and 74%), allied to positive intervention effects (46% and 56%) recorded by the *forecast model* can be interpreted as suggestive of a significant effect associated with the modelled intervention.

Whilst there is evidence of the *NPPF* being cited as a material consideration in developments approved under appeal to central government from October 2012 (DCLG, 2012b), based upon both the structural time scales inherent to the planning process (Ball et al., 2009; Shelter, 2019) and the minimal number of such appeal cases, the reported increase in loss during the transitional period is unlikely attributable to the implementation of the revised planning framework. The outlined would suggest the transitional period most likely reflects the continuation of the collaborative influence of both the previous policy regime and changes to economic circumstances.

Although there is no directly equivalent research against which to assess the significance of the reported intervention effect, comparison can be drawn with general *ITS* research. Based upon nine studies relating to various forms of legal or procedural adjustments, effects ranging from *4%* (Barone-Adesi et al., 2011) to *78%* (Devkaran and O'Farrell, 2015) were termed as such. Whilst conversely, those which assessed there to have been no indication of impact, relied upon intervention effects of less than *1%* (Ramirez and Crano, 2003; Harper and Bruckner, 2017). It must be born in mind that policy effects should be considered within the specific context to which they apply, but the estimated intervention effects recorded from this research can be deemed to reflect a material effect upon green space area.

Reasons for the outlined change can be speculated upon within the context of the provisions of the revised planning framework. However, individual elements must be understood as constituents of a complex structure which interacts with and is influenced by a number of socio-political factors (Hersperger et al., 2018), including growing political pressure to resolve an exacerbating housing crisis (Mulheirn, 2019).

As discussed previously, whilst many of the provisions within the framework can be understood semantically to differ little from previous systems (Davoudi, 2011; Haughton and Allmendinger, 2013), the joint effects of the omission of clarity around key details (Sibley-Esposito, 2014) and implicit change in tone (Conservative Party, 2010) could account for the increased loss in the *post-policy* period. This supposition is supported by Sibley-Esposito (2014), who reported governmental recognition that the intentions of the policy were commonly misinterpreted at a local level, where developments were approved on land eligible for protection.

Whilst across both approaches significant intervention effects were recorded, reported differences are worthy of note. In accordance with expectation the intervention effects associated with the '*construction normalised*' data were lower than the non-normalised equivalents. There is an implication as such, that in relation to the '*green space loss ratio*' data the increased rate could be attributed to total development. This would appear to be corroborated by national residential development data, which showed a sustained increase from 2014 (MHCLG, 2020a) and may be deemed to support one of the original intentions outlined for the revised framework (Cabinet Office, 2010).

The issue outlined above highlights the importance of data which accounts for other drivers of change (referred to in some research as additionality), but is not commonly applied to planning policy research (Morrison and Pearce, 2000). Whilst economic data has previously been considered as a variable within regression models (Kasraian et al., 2019), the complex relationship between economic circumstance, construction and planning applications (Edmund et al., 2009; Marrs, 2019) could not be reliably captured. Therefore, data which can explicitly control for the influence of confounding variables provided enhanced causal inference (Morrison and Pearce, 2000).

Despite the strength of the results, it remains difficult to discern the impact which can be associated with the intervention from other potential factors. Identified as a common issue in regards to the complex systems in which policies operate (Daviter, 2019), particularly for planning where multiple outcomes may be intended (Hersperger et al., 2018).

The existence of a persistent and increasing trend may suggest there was limited direct effect associated with the isolated impact of appeal decisions in the absence of current local plans, which allocate sufficient land for housing need (Sibley-Esposito, 2014). Were such to have been influential an argument can be made data would reflect an initial peak followed by a gradually decreasing trend thereafter as Authorities updated relevant documents. However, such inference is difficult to verify as it was evidenced that over a quarter of Authorities did not have a valid plan in place by 2018 (Lichfields, 2019) and rates of appeal were shown to increase between 2015 and 2018 (MHCLG, 2019).

Where the data accounted for total residential development, there remained a significant sign of a policy effect. Results indicated that on average the area of green space per hundred-thousand new residential buildings was 45% larger than under the counterfactual scenario. This could suggest a change to both the types and density of development in the *post-policy* period.

Research has previously shown, where not constrained by urban boundaries, residential development tends to be of a lower density (Bibby, 2009). It can be speculated this may be attributable to the dominance of free-market principles upon the residential sector (Slater, 2016), with evidence of lower land prices (Livanis et al., 2006), concomitant reduced costs associated with remedial works (De Sousa, 2000) and the effect of the proximity of large areas of green space upon house prices (Morancho, 2003). This can be interpreted as suggesting that the significantly increased loss of green space under the revised framework is associable with a transition from a focus upon densification (Baing, 2010) to urban expansion. However, the outlined supposition cannot be verified based upon the existing research.

5.4.2 Strengths and Limitations

In the absence of a viable research control, *Interrupted Time Series* analysis represented a strong quasi-experimental alternative (Wagner et al., 2002; Fretheim et al., 2013; McDowall and McCleary, 2014; Bernal et al., 2017), which had been applied extensively to other areas of policy research, but not previously used in regards to planning and development. This approach made all reasonable attempts to account for patterns, which existed in the data prior to the implementation of the revised policy, thus enabling the most robust inferential analysis available in the circumstances (McDowall and McCleary, 2014; Lopez Bernal et al., 2019)

By formally testing for *stationarity*, *autocorrelation* and *seasonality*, which contributed to model choices, it was ensured that some of the key threats (Turner et al., 2019) to which such analyses are often susceptible were mitigated against (Ramsay et al., 2003; Jandoc et al., 2015; Harper and Bruckner, 2017). Neither seasonal nor cyclical components were identified as present across all data. Whilst, the adoption of first order polynomial *dynamic linear models* in the *forecast* approach accounted for both *non-stationarity* (West, 1995) and *autocorrelation* (Fei et al., 2011). Whereas, auto-correlated features were explicitly incorporated into the *generalized least squares segmented regression*, with the dummy 'time' and 'trend' variables controlling for relevant linear patterns (Lane and Hall, 2019). Furthermore, in each instance the absence of autocorrelation in the residuals was tested for and confirmed during analysis.

Despite applying relevant data controls as discussed above, the *ITS* approach remains vulnerable to historical bias (Bernal et al., 2017). In the absence of a comparative control group, there are limited means by which to exclude the identified change reflecting the effects of an external event occurring concurrently with the policy change (Linden, 2017).

This concern is increased by the existence of an extended transitional period in which there is greater scope for external factors to influence the data (Galster et al., 2004; Penfold and Zhang, 2013). In comparable *Interrupted Time Series* analyses the maximum delay between an intervention and its effect was 6 months (for example Lane and Hall (2019)). However, a strong evidential basis was presented with which to support the application of such a lengthy delay (Callcutt et al., 2007). Assessments of the time between approval of planning decisions (made under the policy at that time) and the completion of development estimated a range of between 10 months (Lichfields, 2016) and 3.2 years (Callcutt et al., 2007).

In this instance, the risk of historical bias materially affecting the reported intervention effect also appears unlikely, primarily due to relevant data controls. The time-scales which determine development (Callcutt et al., 2007; Lichfields, 2016; Shelter, 2019) (even if one assumes such to have been reduced under the *NPPF* as intended (Paterson, 2012)) would require a confounding event to have taken place between 2009 and 2011. The most likely identifiable event within this time-frame was the economic recovery, with 2014 identified as the year in which national GDP returned to pre-recession levels (ONS, 2018a). However, the same statistical analysis noted that despite nascent signs in 2013, the construction sector did not fully recover until 2015 (ONS, 2018a). In any event this influence was notionally accounted for through the analysis of separate '*construction normalised*' data, which retained significant reported effects.

Whilst, the outlined can be considered to suggest the research has a relatively high degree of internal validity (Biglan et al., 2000), the extent to which it can be considered to offer generalizable outcomes is more difficult to establish (Penfold and Zhang, 2013). As the data does not relate to the entire population, the derived inferences can only reliably be reported in regards to the sample (Biglan et al., 2000). Said sample constitutes around 14% of the total population and was designed to offer a broad range of Local Authority Area types, but cannot be considered to replicate a truly representative sample due to the high degree of variability between such. Therefore, inferences should be considered cautiously when applied to the entire country.

However, by employing a robust sample of Local Authority Areas with a diverse profile, in regards to which systematic bias is deemed unlikely, the strong evidence derived from this research can be considered suggestive of a general trend. With Dallimer et al. (2011) previously identifying hugely variable impacts between different Local Authorities, future research may be required to confirm this.

With appropriate model choice identified as a critical factor in *ITS* based research (Wagner et al., 2002), the adoption of two distinct modelling approaches can be contended to offer additional inferential support (Harrop and Velicer, 1985). Applied to the same data, each reflected positive intervention effects in the *post-policy* period. Additionally, in each instance comparison was made with alternative models and assessed accordingly.

Additionally, due to the highly stochastic nature of the data and some uncertainty in regards to the dates at which developments may have been approved, the use of a *dynamic linear modelled post-policy* period, which attempts to account for such should be considered to increase the strength of analysis (Brodersen et al., 2015; Brodersen and Hauser, 2020).

All inferences must be considered as constituents of synergistic relationships, in regards to which the attribution of increased rates of development upon green space to the policy reforms alone remain difficult (Galster et al., 2004). However, many of these factors, such as the growing political pressure to resolve an exacerbating housing crisis (Mulheirn, 2019), should be understood as influential both directly to the policy reform and indirectly to its subsequent application.

5.4.3 Implications

With green space the subject of increasing developmental pressure globally, it is vital that the implications associated with policy provisions are understood (Alexander, 2016; Hersperger et al., 2018). The *Interrupted Time Series* analysis methodology applied in this research addressed one of the core issues identified by Morrison and Pearce (2000), establishing a counterfactual scenario, representing the outcome in which the policy did not come into force.

Consequently, where data exists to act as an indicator of policy impact (often a conceptually difficult stage in conformance based evaluation (Morrison and Pearce, 2000)) the *ITS* method could be utilised to assess the outcomes of both national and local planning provisions.

The outcomes indicated by this and previous research (Dallimer et al., 2011) should be used to inform evaluation within the policy cycle, providing evidence for reform (Jann and Wegrich, 2007). When the *NPPF* was the subject of revision in 2018, responses to statutory consultation raised concerns that it had failed to adequately balance environmental needs (MHCLG, 2018a). Similar issues were identified by the *Campaign to Protect Rural England* around the failure to contribute to sustainable development in submission to the *Raynsford Review of Planning* (CPRE, 2017). CPRE (2017) reported an increase in low density residential development leading to a loss of green space. However, without clear quantitative evidence the organisation's position was difficult to substantiate.

This research substantiated the outlined and analogous concerns (RSPB, 2011) and can be considered to support requests that additional provisions were included to ensure the unnecessary loss of undeveloped land was guarded against (MHCLG, 2018a).

It can further be used to inform future *ex ante* evaluation, responding to a common issue relating to the lack of high granularity data (Smismans, 2015). Whilst predictive modelling of future scenarios under the different policy approaches could incorporate the outcomes as a means of augmenting existing data profiles.

The extent of the increase in the loss of previously undeveloped land raises significant concerns in relation to a variety of ecosystem services (Bolund and Hunhammar, 1999). Advocating recommendations made in the *Raynsford Review of Planning*, it suggests the need to evolve a legal duty for the planning system to deliver sustainable development, including management of the "*use, development and protection of land*" (TCPA, 2020).

5.5 Conclusion

This research aimed to broaden understanding of the impacts upon green space associated with planning policy reforms, using the *Localism Act 2011* and *National Planning Policy Framework* as an example. Strong evidence was presented of an increased area of land having been subject to development during the *post-policy* period than would have been anticipated under the previous framework.

Based upon the interpretation of the revised system as representing a less regulated approach to development (Sibley-Esposito, 2014), it suggests such may lead to persistent and increasing loss of environmentally important green space. Whilst some caution may be deemed prudent in light of the potentially confounding effects of external factors and uncertain elements of the data, the capability of *dynamic linear models* to account for such can be considered to offer a more robust insight.

However, there is evidence to suggest the effects upon green space may be different based upon its location within urban boundaries or the peri-urban fringe (Dallimer et al., 2011). Therefore, analysis which provides understanding of the impact of policy change upon different types of green space land should be deemed a core element of future research.

CHAPTER 6

The Inviolable Idyll?

Quantitatively Analysing the Policy Impact upon Rural Land

"The coffin of our English dream,
Lies out on the village green,
While agri-barons CAP in hand,
Strip this green and pleasant land,
Of meadow, woodland, hedgerow, pond,
What remains gets built upon."

Country Life
Knightly (2003)

Mixed within the ancient broad-leaved woodland landscape of the *High Weald Area of Outstanding Natural Beauty* (Anderson, 1981) are situated a verdant patchwork of fields connected by diverse hedgerows (Bannister, 2017), which form an interconnected ecosystem for a variety of species, including White Admiral butterflies [*Limenitis camilla*], Eurasian Treecreepers [*Certhia familiaris*] and Wood Sorrels [*Oxalis*] (Patmore, 2000).

The retained woodland constitutes 7% of the total area contained within England and has occupied the site continuously for over 400 years at least (The High Weald AONB, 2020). Whilst the surrounding fields have provided agriculture, commons and pastures since medieval times (Bannister, 2017). Surrounded by this 146,000 Ha area is the town of *Crowborough*, an urban island in a vast sea of green (Anderson, 1981). Due to this location within a designated *AONB* the town has been to some extent constrained by a natural rural boundary.

However, in 2020 a 6.5 Ha site, consisting of 4 fields delineated by native hedgerow, part of which remains common land was approved for development

(Wealden District Council, 2020), marking the incursion of the urban into the rural fringe. Such rural hinterlands are envisioned as the next key battleground in the inexorable march of urbanisation (Gant et al., 2011), with regulation through policy one of the tools to support containment (Millward, 2006). The threat to the *High Weald* may be emblematic of a wider trend and presage a greater developmental loss than previously evidenced.

6.1 Introduction

Although somewhat incongruous with widely held perceptions of England as a predominantly urban country (Lock and Cole, 2011), as of 2011 only 10.6% [1,382,187 Ha] of total land cover was recorded as such (Watson and Albon, 2011). Additionally, it can be noted that said urban designation did not directly equate to built land, with urban green spaces, blue spaces and private gardens recorded as accounting for almost three-quarters of the recorded area (Watson and Albon, 2011). Despite this seeming abundance of undeveloped land, developmental pressure upon rural areas represents both a politically emotive issue (Gant et al., 2011) and reflects an increasing global concern (Bart, 2010).

Within the context of the UK, the inviolability of rural land cannot be extricated from the cultural significance of the '*rural idyll*' (Harrison and Clifford, 2016), which evolved in response to the rapid urbanisation associated with the Industrial Revolution (Žmolek, 2013) and has influenced public perception of planning policy since its inception (Cullingworth and Nadin, 2003). The adoption of 'Green Belts' as a means through which to protect rural land from urban expansion represents one of the founding principles of modern planning (Elson et al., 1993). However, as the pressure of urbanisation continues to grow and the concomitant restricted supply of land has become linked to an unprecedented crisis in regards to access to housing (Cheshire, 2013), the continued retention of 'Green Belt' land has become the subject of debate (Papworth, 2015).

This discourse represents one of the fundamental issues in regards to planning policy, as it attempts to balance the impacts associated with the constraint of urban areas against those associated with expansion into the rural fringe (Ståhle, 2010). Having ostensibly been characterised by a prolonged period of focus upon urban densification (Cullingworth and Nadin, 2003), the *Localism*

Act 2011 and *National Planning Policy Framework* were portrayed as a radical shift towards urban expansion (Sibley-Esposito, 2014).

However, this contention could largely be attributed to a perceived diminution in regards to the protection afforded to 'Green Belt' land (Sibley-Esposito, 2014), claimed by the *Campaign to Protect Rural England*. Whilst governmental data related to both rates of development and applications to build upon 'Green Belt' sites have been used to support this view (CPRE, 2018), there has been no quantitative analysis to assess the extent to which the policy may threaten protected areas. Furthermore, there has been limited analysis related to wider rural land.

This research therefore, builds upon the foundations outlined in **chapters 4** and **5**, which cumulatively established the existence of a structural shift related to a strong intervention effect, evidencing the occurrence of increased development upon green space land. However, neither enabled the exploration of the extent to which developmental loss related to designations of urban and rural land, considered crucial to the development of a conceptual model of policy as a regulator of urban expansion (Dallimer et al., 2011).

6.1.1 Primary Research Aim

The encroachment of urban areas into previously undeveloped rural fringe land represents a burgeoning issue in a number of rapidly developing nations (Yang and Jinxing, 2007), as a result of the pressures of population growth and economic migration (Colantoni et al., 2016). Effective control of this phenomenon is considered essential to both local (Zhao, 2010) and global sustainability (Bart, 2010). With lessons learnt from policies intended to guide urban compaction in Nations that have previously undergone analogous periods of growth assumed to be an important tool to support this endeavour (Stead, 2012).

However, the consequences associated with common strategies utilised to restrict urban expansion have become the subject of debate (Bengston and Youn, 2006a). Regulatory 'Green Belts' have been shown to have merely displaced development to other natural areas (Bae and Jun, 2003) and broader policies of containment have been cited as a significant factor in the UK housing crisis (Cheshire, 2013).

Similarly to other analyses relating to drivers of land use change, to date the majority of research has relied upon satellite imagery as a primary data source, which may fail to identify more subtle elements of change (Plieninger et al., 2016), explicitly in the rural fringe (Gallent, 2006). Furthermore, quantitative assessments of policy effect have been limited in methodological approach and are contended to offer limited inferential strength (Morrison and Pearce, 2000). This debate can therefore be augmented by both novel data sources (such as highly granular vector data (Smith et al., 2007)) and robust inferential methods (McDowall et al., 2019).

It is contended both individual provisions within the *National Planning Policy Framework* and the general tone it sets are indicative of a paradigm shift in planning policy from a focus upon densification, in which development is restricted to existing urban boundaries, to the enablement of expansion into proximate rural areas (Dallimer et al., 2011; Sibley-Esposito, 2014; Slade, 2018). This was particularly associated with the tacit removal of a 'brownfield' first provision (Sibley-Esposito, 2014), which had been evidenced to have contained development under the prior policy framework (Ganser and Williams, 2007). Although media focus has primarily related to a purported diminution in the protection afforded to 'Green Belt' land.

It is therefore the intention of this research to investigate the extent to which this supposition is supported by quantitative analysis of green space loss data. More formally the research can be considered to have been designed to address the following research question.

Research Question 3: Do analyses of rates of development upon green space offer insights in regards to the extent to which the revised planning framework can be characterised as enabling urban expansion?

To address this research question two elements were adopted. The first focused upon the estimation of an intervention effect in regards to the occurrence of development on 'Green Belt' land, responding to the need for a robust empirical analysis to augment prior reports of effects (CPRE, 2018). Whereas the second was designed to assess the impact upon the urban-rural fringe, commonly omitted from research, but deemed a political priority (Gallent, 2006). In this approach, the work directly builds upon the focus of preceding research undertaken by Dallimer et al. (2011), in which rates of development both within and outside urban areas were assessed under the prior policy framework. In order to enhance the inferential validity of the study, separate intervention effects were derived for '*green space loss*' and 'brownfield' land.

6.1.2 Contribution

The final contribution of this thesis investigated the impact of policy change upon the spatial pattern of development in relation to existing urban boundaries, using methods consistent with established policy impact evaluation (Bernal et al., 2017). Through analysis of the impacts upon designated 'Green Belt' and in relation to urban boundaries it developed an empirical evidence base to inform understanding of provisions intended to promote densification or urban expansion. It evidenced an association between the adoption of a policy which could be considered broadly more permissive of development and a rapid alteration to the distribution of development, suggestive of increased development within the rural fringe. This validates existing research (Dallimer et al., 2011; Mu et al., 2016) and informs the wider development of theories relating to the role of policy in regards to patterns of development.

The analysis represents a response to the the demand for research to be undertaken with regard to the land impacts associated with different approaches to densification as identified by Dallimer et al. (2011). It adopts an analogous set of primary indicators of land change (green space and 'brownfield') and relates to a policy interpreted as a mechanism discouraging of urban expansion in the same research. Furthermore, considered in conjunction with this preceding work the research contributes towards the expansion of a theoretical basis with which to inform the balance between developmental needs and green space conservation.

6.1.3 Motivating Examples

Prior to the research undertaken in regards to the outlined aim, this section presents a motivating example based upon existing governmental records related to rates of development on designated 'Green Belt' land. Whilst the outlined data has informed popular debate around the impact of the revised framework (Marrs, 2018), methodological issues cast doubt as to the validity of the outcome.

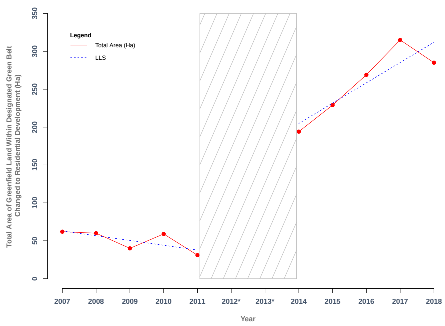

Figure 6.1: Source: MHCLG (2012)

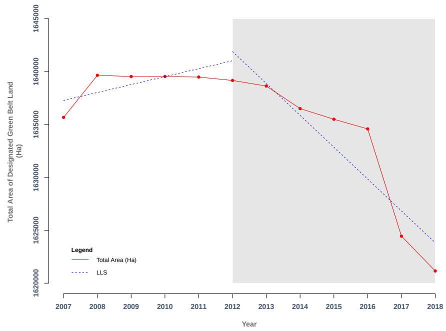

Figure 6.2: Source: MHCLG (2019e)

The *Campaign to Protect Rural England* [*CPRE*] reported that from analysis of governmental records pertaining to the rate of residential development within the designated 'Green Belt', it was "*highly likely that the NPPF*" had resulted in increased loss of green space (CPRE, 2018). Said data is reproduced above [figure 6.1] based upon the same original data (MHCLG, 2012), which was used by *CPRE*. A simple ordinary least squares line of linear regression for the periods both before and after the implementation of the revised legislative and policy framework was fit to the data and would appear to suggest that a change occurred during the intervening period.

Between years 2014 and 2017 an average of 251 Ha of green space were developed upon per annum within the 'Green Belt'. This can be compared to a recorded average of 50 Ha per annum between years 2007 and 2011. Interpreted graphically it appears evident that there has been a significant change in both the intercept and slope within the second period.

However, it should crucially be noted that the methodological approach to identifying the area of land upon which development occurred was significantly amended in 2012 (DCLG, 2015a). As a result of which the area of land identified as having changed would inevitably be much higher than that recorded under the previous regime (DCLG, 2015a). Consequently, relevant data should be considered unreliable for comparison, with explicit advice not to interpret such as evidence of temporal change in rates. Whilst the effect of the methodology upon land within the designated 'Green Belt' may be considered less likely to be affected by this alteration, it requires more robust statistical support.

Supplemental data based upon separate governmental records of the total area of land designated as 'Green Belt' in England can be considered to strengthen the *CPRE*'s assertion in spite of the outlined methodological concerns. MHCLG record the total area of land designated as 'Green Belt' per annum, based upon data submitted by individual Local Authorities (MHCLG, 2019c). Whilst changes in area merely reflect the removal of the legal designation from land rather than that development has occurred, said data can be considered to offer some insight into the effects of the planning system as it generally precipitates future development.

Interestingly, the data for England shows a rapid increase in the area of land from which the designation was removed between 2016 and 2017 in particular, allied to a more general pattern associated with the period after the implementation of the *NPPF* [figure 6.2]. Comparison of recorded average change between the period prior (2007 - 2012) and subsequent (2012 - 2019) to the implementation, record an increase of around 1,530 Ha and decrease of 2,618 Ha respectively. Within reporting published in 2018, the outlined data was supplemented by analysis of planning applications, which showed an increase from 27 applications in 2009 to over 155 in 2019 (CPRE, 2018). Similarly to the other data discussed in this section, alone the above does not offer robust inference (McDowall et al., 2019), but portrays a general pattern of increased land loss. Therefore, supplementing the existing body of evidence with analysis of data derived from a consistent methodology may therefore be considered essential to developing inference through which to augment understanding of the role of policy.

6.2 Chapter Structure

This chapter is hereafter structured as follows. **Section 6.3** describes the method undertaken in this research, including the temporal range, two distinct samples and five univariate time series upon which it is based. The analytical process employed to conduct *Interrupted Time Series Analysis* is outlined. Results [section 6.4] are structured in two parts, around the 'Green Belt' and urban boundary analyses. **Section 6.5** discusses the key findings, relative strengths and weaknesses associated with the applied methodology and implications of the research. With conclusions presented in **section 6.6**.

6.3 Methodology

Responding to the need to utilise robust quantitative analytical methods to inform the development of a conceptual model of policy impacts upon land use (Plieninger et al., 2016), the methodology outlined within this research applies *Interrupted Time Series* Analysis (Bernal et al., 2017), using *dynamic linear models* (Brodersen et al., 2015). The aforementioned approach was validated in **5** and extends the use of methods proposed in Ramachandra (2019), whilst complying with recommendations for policy analysis (HM Treasury, 2020b).

Analysis is conducted in two stages relating to the occurrence of green space loss within designated 'Green Belt' and subsequently outside existing urban boundaries. With both collectively intended to provide insight into the effects of the subject policy change upon patterns of development. In regards to the research relating to urban boundaries three distinct indicators of land change were utilised, in the form of '*green space loss*' within the urban boundary, '*green space loss*' outside the urban boundary and indicative 'brownfield' loss within the urban boundary.

The methodology hereafter describes relevant samples and datasets, prior to illustration of the analytical methods undertaken.

6.3.1 Sample

Two distinct samples were utilised in regards to the analyses of the estimated policy impacts upon both land within the 'Green Belt' and in relation to indicative urban boundaries respectively.

Where related to relevant urban boundaries, the sample comprised 42 Local Authority Areas in England, derived through an adapted maximum variation methodology (Cohen and Crabtree, 2006) **section 3.3**. It consists of a geographically dispersed range of 21 designated 'urban' and 21 designated 'rural' authorities, reflective of diverse economic and physical profiles (Bibby and Brindley, 2013).

However, the 'Green Belt' sample was restricted to a subset of twenty-two, which were identified as containing relevant designated land in 2007. In total, the outlined subset sample contained a 'Green Belt' area of 2,120,818km^2, ranging from a mere 0.2km^2 in Blaby to 339,776.4km^2 in regards to Leeds (based upon MHCLG (2019b) 'Green Belt' data). Of the twenty-two authorities which constitute this sample, fourteen are classified as 'urban' and eight as 'rural' (Bibby and Brindley, 2013). This disparity can be attributed to the association between 'Green Belt' designation and existing urban boundaries (Garton and Barton, 2019).

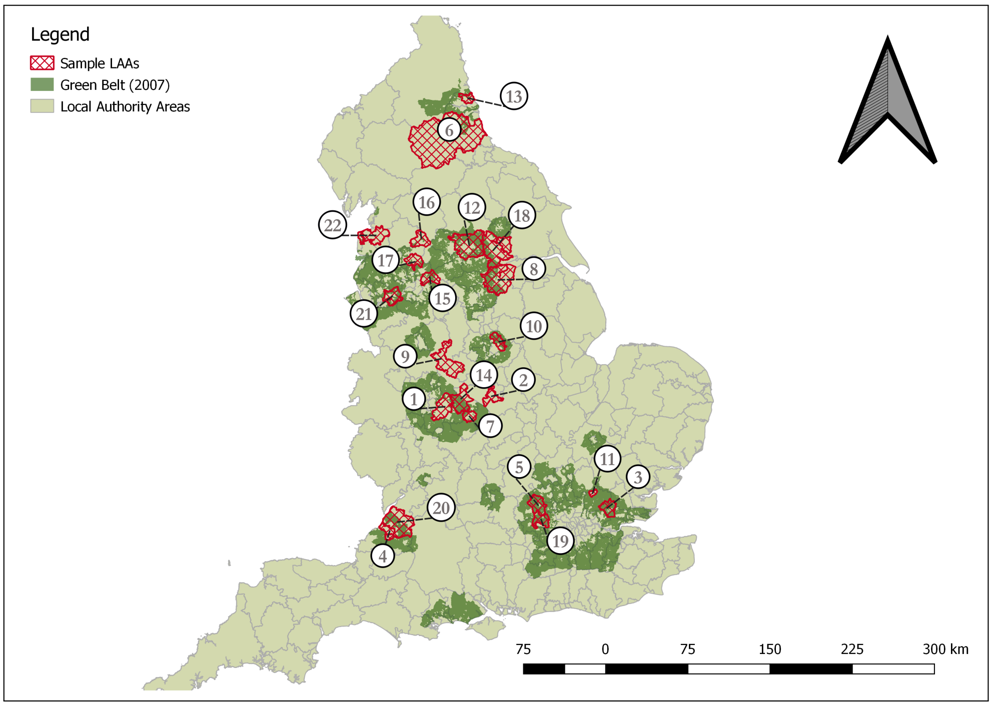

Figure 6.3: Data Sources: Ordnance Survey (2018b); MHCLG (2019c) Sample Local Authority Areas with designated 'Green Belt' (2007).

	Local Authority	Green Belt Area (km^2)		Local Authority	Green Belt Area (km^2)
12	Leeds	339776.4	**15**	Oldham	62556.9
8	Doncaster	232559.8	**1**	Birmingham	41888.8
20	South Gloucestershire	232300.9	**17**	Rossendale	31732.1
18	Selby	192828.4	**7**	Coventry	30324.3
5	Chiltern	173801.6	**16**	Pendle	20733.4
14	North Warwickshire	172843.9	**13**	North Tyneside	16609.5
3	Brentwood	137498.0	**22**	Wyre	7528.3
19	South Bucks	123441.7	**11**	Harlow	6370.8
21	Warrington	114220.7	**4**	Bristol, City of	6086.0
10	Gedling	90111.8	**9**	East Staffordshire	393.3
6	County Durham	87211.0	**2**	Blaby	0.2

Table 6.1: Area of 'Green Belt' (2007) for each sample LAA based upon MHCLG (2019b) data.

6.3.2 Temporal Range

Throughout this section of research all relevant data consist of 48 observations obtained at quarterly intervals between quarter 1 of 2007 and 4 of 2018.

In accordance with prior analyses [**chapter 5**], data were segmented into common *pre-policy* (Q1 2007 to Q4 2011), *transitional* (Q1 2012 to Q4 2013) and *post-policy* (Q1 2014 to Q4 2018) periods to support *Interrupted Time Series* analysis (Lane and Hall, 2019). The identification of which were informed by evidence outlined in detail in **section 4.3.3.1** and can be considered to be broadly based upon an average two-year delay between planning approval and the completion of development (Shelter, 2019).

6.3.3 Green Space Loss Data

Green space data comprises over 300,000 geospatial polygons derived from *OS Mastermap*® digital topographic data (Ordnance Survey, 2017). Each depicts areas recorded as buildings and associated infrastructure (including private gardens), manmade surfaces or sites undergoing development, which were identified as indicative of the existence of previously undeveloped green space at the prior time interval.

Accordingly, each green space loss area polygon consists of geometric attributes (such as area (m^2), shape and location), both pre-change and post-change classification criteria and a time of change identifier (quarter and year).

6.3.4 Change to Land Within Designated 'Green Belt'

'Green Belt' data were sourced through the governmental open data platform (MHCLG, 2019b). Said data consists of collated geo-spatial shapefiles, depicting both the geometric attributes and location of designated 'Green Belt' recorded at regular intervals and accessed for the following available time periods:

- 2003
- 2007
- 2007 - 2008
- 2008 - 2009
- 2009 - 2010
- 2010 - 2011
- 2011 - 2012
- 2013 - 2014
- 2014 - 2015
- 2015 - 2016
- 2016 - 2017
- 2017 - 2018

It should be noted data was not available for any calendar year between 2003 and 2007 or reporting year 2012 - 2013.

Due to the regular revision of 'Green Belt' boundaries (Garton and Barton, 2019) two distinct measures relating to the area of development within such were adopted. They relate to land which was designated as such at the time of the change and land from which the designation was removed prior to the occurrence of the change.

The first is concerned only with the occurrence of development within areas of land which were designated as 'Green Belt' at the time of the change (based upon the most recently available data). Accordingly it can be understood to reflect the spatial intersection between the area of '*green space loss*' recorded in regards to a time (t) and land registered as 'Green Belt' at the last time (i) prior to or at time $t - 1$.

For a time series $t_0, ..., t_{+47}$, loss within designated 'Green Belt' ($GSGBL$) is;

$$GSGBL_t = GSL_t \cap GB_i \qquad \text{for} \quad t = 0, ..., 47 \tag{6.1}$$

where GSL$_t$ is the '*green space loss*' which occurred between times $t - 1$ and t; and GB is land registered as 'Green Belt' in i, where i is the most recent time period in the 'Green Belt' dataset up to time $t - 1$.

Whilst the second also included all development which has occurred upon land from which the designation was removed prior to the change. Methodologically, in relation to the changes which took place during the *pre-policy* period, said data can be understood to reflect the spatial intersection between the ‘*green space loss*’ data and land which was registered as ‘Green Belt’ in any year prior to said change occurring (2003 to 2011). Whereas, for *post-policy* change data, it is restricted to land from which the designation was removed after 2012.

Accordingly the data comprises individual polygons showing the intersection between ‘*green space loss*’, which occurred at time t and land registered as ‘Green Belt’ at any time (i) prior to or at time $t-1$.

For a time series $t_0, ..., t_{+47}$, loss within designated ‘Green Belt’ ($GSGBL$) is;

$$GSGBL_t = GSL_t \cap GB_i \qquad \text{for} \quad t = 0, ..., 47 \tag{6.2}$$

where GSL$_t$ is the ‘*green space loss*’ which occurred between times $t-1$ and t; and GB is land registered as ‘Green Belt’ in i, where i is any time period in the ‘Green Belt’ dataset up to time $t-1$, but greater than t_τ, representing the point at which the intervention occurred.

Figure 6.4: Area of ‘*green space loss*’ which is contained within the ‘Green belt’ boundary.

For example, for an area of green space loss recorded as having occurred in quarter 4 of 2018:

- **'Green Belt' at time of change**: represents the spatial intersection with the 'Green Belt' area recorded in regards to 2017 - 2018.
- **'Green Belt' at any point prior to change**: represents the spatial intersection with any 'Green Belt' area recorded between 2013 - 2014 and 2017 - 2018.

Derived data was aggregated by quarter and subsequently reflects the area of green space loss (m^2) to have occurred across the full sample as a proportion of the total available area of green space (Ha) within the 'Green Belt' at that time (m^2/Ha).

6.3.5 Change to Green space Land Within and Outside of Urban Boundary

The area of green space in relation to urban boundaries is founded upon the dataset outlined in **section 6.3.3** and used previously in **chapter 5**. As such, it should be understood to reflect areas of previously undeveloped land, (classified as 'natural' by *Ordnance Survey* (Ordnance Survey, 2009)), which have been reclassified and are considered suggestive of development having occurred between any two consecutive time intervals in adherence to the outlined methodology.

Relevant urban boundaries were derived from both 2001 (UK Data Service, 2018) and 2011 (ONS, 2019) census data, accessed in spatial vector form from open source governmental repositories. Whilst the technical methodology by which each dataset was produced had altered, both identified urban form as areas of at least 200km^2 of built environment and considered areas within 200m of each other to be contiguous for this purpose (ONS, 2013).

Where the 2001 data had been manually identified and digitised, in 2011 areas were based upon a predominantly automated process whereby land was divided into 50m grid squares and categorised by the percentage of particular land types ("*Buildings and Glasshouses, Areas of tarmac, concrete and Primarily gardens*") contained within (ONS, 2013). Although direct comparison between the two boundary areas is advised to be undertaken with caution, data were evidenced to be broadly consistent [figure 6.5] (ONS, 2013) and deemed to offer the most suitable resource available.

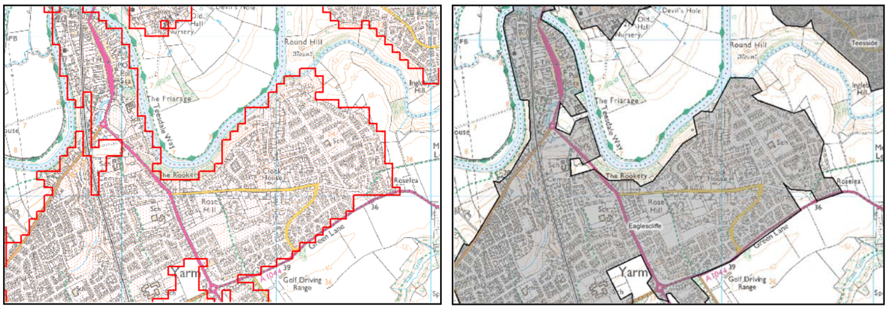

Figure 6.5: Source: ONS (2013)
Graphical comparison of 2011 grid based boundary (left) and 2001 manually digitised equivalent (right)

The resultant research data therefore, represents two univariate time series.

Change Within the Indicative Urban Boundary

Green space loss within the urban boundary can be characterised as the area of spatial intersection between land that was classified as green space at time $t-1$, but had become 'developed' by time t; and the relevant built-up area boundary (2001 for the *pre-policy* period and 2011 for the *post-policy* period).

Therefore, interpreted mathematically it should be understood as;

$$UGSL_t = GSL_t \cap UB_i \quad \text{for} \quad t = 0, ..., 47 \tag{6.3}$$

where GSL_t is the '*green space loss*' which occurred between times $t-1$ and t; and UB is land contained within the urban boundary in i; where i is the relevant urban boundary.

Change Outside of the Indicative Urban Boundary

Corresponding green space loss outside the urban boundary can be characterised as the area of spatial difference between land that was classified as green space at time $t-1$, but had become 'developed' by time t; and the relevant built-up area boundary (2001 for the *pre-policy* period and 2011 for the *post-policy* period).

$$RGSL_t = GSL_t \setminus UB_i \quad \text{for} \quad t = 0, ..., 47 \quad (6.4)$$

where GSL_t is the '*green space loss*' which occurred between times $t-1$ and t; and UB is land contained within the urban boundary in i; where i is the relevant urban boundary.

Figure 6.6: Inside extant urban boundary

Figure 6.7: Outside extant urban boundary'

As with previous data, the final metric upon which analysis was undertaken consisted of two aggregated green space loss figures reflecting 48 area observations as a proportion of the relevant area of green space either contained within or outside of the existing urban boundary at the time of the change (m^2/Ha).

6.3.6 Change to Indicative 'Brownfield' Land Within Urban Boundary

In addition to the green space data outlined above, an indicative 'brownfield' metric was also developed in order to more closely resemble comparable research (Dallimer et al., 2011) and act as a viable control (Cruz et al., 2017).

The identification of 'brownfield' development was more complex than the transition between green space and built form. As a result this data jointly represents any artificial surface (classified as either 'manmade' or 'multiple' (Ordnance Survey, 2017)), which was recorded as having become 'unclassified' between any two consecutive time intervals, allied to any previously removed 'natural' surfaces, which were identifiably related to existing or previously removed built environment, upon which subsequent development occurred.

Figure 6.8: Data Source: Ordnance Survey (2018b).
Example of ‘brownfield’ change identified through re-classification from built form to ‘unclassified’.

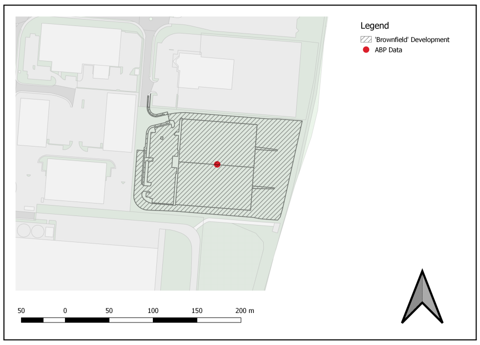

Figure 6.9: Data Source: Ordnance Survey (2018b).
Example of ‘brownfield’ change identified through indicator of prior development.

The method by which the outlined ‘brownfield’ data were derived did not enable the reliable identification of areas which underwent change without being re-classified and should therefore not be considered an exhaustive resource. However, as a general indication of rates of change on land which had previously been developed it was deemed to offer suitable accuracy and corresponded to methods previously used in academic research (Dennis et al., 2018).

The subsequent data can thus be understood to reflect the area of spatial intersection between land that was classified as ‘brownfield’ at time $t-1$, but had become ‘developed’ by time t; and the relevant built-up area boundary (2001 for the *pre-policy* period and 2011 for the *post-policy* period).

$$UBL_t = BL_t \cap UB_i \quad \text{for} \quad t = 0, ..., 47 \qquad (6.5)$$

where BL_t is the brownfield loss which occurred between times $t-1$ and t; and UB is land registered as contained within the urban boundary in i; where i is the relevant urban boundary.

Aggregated ‘brownfield’ data reflected the area of identified land to undergo development as a proportion of the land cover, which was not classified as green space at the time of the change (m^2/Ha).

6.3.7 Analytical Methods

Adopted methods were based upon *Interrupted Time Series* Analyses using *dynamic linear models* (Petris and An, 2010). Prior to formal analysis being undertaken all data was assessed for the existence of '*seasonal*' patterns and '*autocorrelation*' using designated functions within *R* (R Core Team, 2019). Neither *seasonality* nor *autocorrelated* structures were identified within either the 'Green Belt' or urban boundary data.

The method consisted of five stages, repeated for each of the five distinct analyses. Initially data was segmented into relevant periods, in regards to which appropriate models were fit to the *pre-policy* and subsequently *post-policy* periods. Finally, intervention effects were derived for each *post-policy* observation, reflecting the difference in area between the modelled *post-policy* period and counterfactual scenario based upon the extrapolation of the *pre-policy* trend (Linden, 2017). The process undertaken can be conceptualised as;

- i. Data segmented into *pre-policy*, *transitional* and *post-policy* periods;
- ii. Appropriate model fit to *pre-policy* period based upon functional test of fit (based upon *MAE* and *RMSE*);
- iii. Extrapolated '*counterfactual*' for *transitional* and *post-policy* periods;

iv. Equivalent model fit to *post-policy* period;

v. Estimated intervention effect calculated between *post-policy* model and extrapolated *pre-policy* prediction.

6.3.8 Segmentation

In all instances data was segmented into *pre-* (2007 to 2011), transitional (2012 to 2013) and *post policy* periods (2014 to 2018), based upon the assumption that there may exist a lag of between 1 and 2 years between planning approval and the commencement of noticeable developmental ground works (explored in section 5.2.2) (Callcutt et al., 2007; Lichfields, 2016; Shelter, 2019).

Therefore, the *pre-policy* period consisted of 20 observations recorded in regards to quarters 1 to 4 of 2007 to 2011. Whilst the *post-policy* comparator ranged from quarter 1 of 2014 to quarter 4 of 2018. The transitional period (from quarter 1 of 2012 to quarter 4 of 2013) was excluded from analysis, but used to assess the validity of the predicted counterfactual.

6.3.9 Pre-Policy Models

For all relevant data sets the *pre-policy* period was initially tested against a variety of model types in which the dependent variable was the relevant land change data. Tested models included *Ordinary Least Squares*; *Generalized Linear Models*; *Autoregressive, Integrated Moving Average*; and *Dynamic Linear Models* (Lane and Hall, 2019) and were analysed for fit based upon *RMSE* and *MAE* values.

Model	*Mean Absolute Error (MAE)*	*Root Mean Squared Error (RMSE)*
'Green Belt' Change (Current)		
Ordinary Least Squares	0.22	0.36
Generalized Linear Model	0.22	0.36
ARIMA (2,1,0)	0.23	0.34
Dynamic Linear Model	**0.20**	**0.31**
'Green Belt' Change (Historic)		
Ordinary Least Squares	0.34	0.56
Generalized Linear Model	0.34	0.56
ARIMA (0,0,0)	0.37	0.58
Dynamic Linear Model	**0.33**	**0.50**
GS Change Inside Urban Boundary		
Ordinary Least Squares	12.32	15.33
Generalized Linear Model	11.23	14.67
ARIMA (0,0,0)	13.20	17.29
Dynamic Linear Model	**7.53**	**10.13**
GS Change Outside of Urban Boundary		
Ordinary Least Squares	0.58	0.81
Generalized Linear Model	0.58	0.81
ARIMA (0,0,0)	0.60	0.82
Dynamic Linear Model	**0.57**	**0.74**
Brownfield Change Inside Urban Boundary		
Ordinary Least Squares	0.98	1.18
Generalized Linear Model	0.98	1.18
ARIMA (0,0,0)	1.06	1.35
Dynamic Linear Model	**0.73**	**0.95**

Table 6.2: MAE and RMSE comparison of prospective pre-policy models (OLS, GLM, ARIMA and DLM)

Based upon relevant outlined comparisons *dynamic linear models* were identified as the best method through which to model the *pre-policy* data in all instances.

Relevant parameters for first order polynomial *dynamic linear model* observation and evolution equations were derived in regards to each data set using maximum likelihood functions (Petris and An, 2010).

$$y_t = F_t\theta_t + v_t, \qquad v_t\ N(0, V_t) \tag{6.6}$$

$$\theta_t = G_t\theta_{t-1} + w_t, \qquad w_t\ N(0, w_t) \tag{6.7}$$

The observation equation, y_t represents the product of the area of '*land loss*' (for each data set), in the form of F_t and the state equation, θ_t, to which a mean zero error is added, v_t. Whilst G_t is the evolution vector, in this instance a 1 by 1 matrix representing time and w_t the underlying state errors assumed to have a mean of zero.

Derived variances were coded to be automatically inserted into relevant models, which were then fit to the '*pre-policy*' data using a *Kalman filter* (Petris and An, 2010). Based upon the outlined modelled system states, the *dlmForecast* function (Petris and An, 2010) was used to obtain the anticipated *transitional* and *post-policy* period future observation values. Relevant 95% prediction intervals were derived for each forecast future observation, assuming normal distributions. An indicative predictive validity was assessed using the observations relating to the *transitional* period (quarters 1 to 4 of 2012), with the prediction interval evidenced to contain the transitional observations in each circumstance.

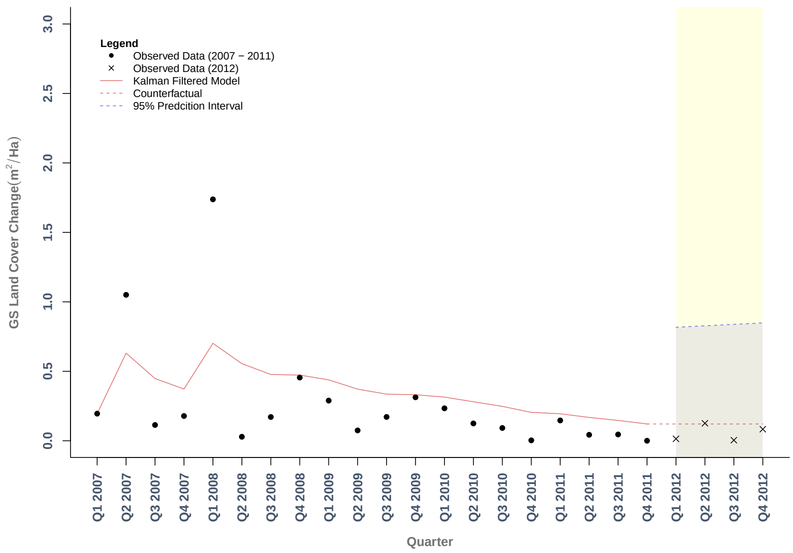

Figure 6.10: Example of *dlm* prediction interval informal validity test based upon green space development within designated ‘Green Belt’

6.3.10 Post-Policy Models

The *post-policy* period was both modelled using the *dynamic linear model* approach (Petris and An, 2010) and retained as raw observations in order to facilitate comparison between the two approaches.

Statistical comparison was derived in regards to the fit of the models between the *pre-* and *post-policy* periods. Generally, due to larger variance in the *post-policy* periods models reflected a worse fit and may be considered likely to potentially underestimate the intervention effect as a result. However, in the example of brownfield change the alternative was true, suggesting inferred intervention effects may over-estimate.

	Pre-Policy	Post-Policy
'Green Belt' Change (Current)		
Mean Absolute Error (MAE)	0.20	1.07
Root Squared Mean Error (RMSE)	0.31	1.36
'Green Belt' Change (Historic)		
Mean Absolute Error (MAE)	0.33	1.09
Root Squared Mean Error (RMSE)	0.50	1.40
GS Change Inside Urban Boundary		
Mean Absolute Error (MAE)	7.53	22.94
Root Squared Mean Error (RMSE)	10.13	30.13
GS Change Outside of Urban Boundary		
Mean Absolute Error (MAE)	0.57	7.28
Root Squared Mean Error (RMSE)	0.74	7.44
Brownfield Change Inside Urban Boundary		
Mean Absolute Error (MAE)	0.73	0.17
Root Squared Mean Error (RMSE)	0.95	0.23

Table 6.3: Table recording comparative statistics (MAE and RMSE) between *pre-* and *post-policy* models.

In spite of the outlined concerns the approach was deemed to offer robust analysis of the change which occurred in the trends between the two periods and can be considered likely to account for underlying external influences (Ahn et al., 2017). The adoption of a common approach also allows for clear comparison between comparable elements of research.

6.3.11 Intervention Effects

In *Interrupted Time Series* Analysis results are commonly referred to as an 'intervention effect' (McDowall et al., 2019), which is determined either directly or indirectly through comparison between the predicted counterfactual, which assumes the continuation of the *pre-policy* trend, and modelled *post-policy* period.

For this research, the reported intervention effects were estimated for each time interval in the *post-policy* periods as the difference between the maximal values of the counterfactual scenario (based upon a 95% prediction interval) and the modelled *post-policy* equivalents (Mohr, 1995; Wagner et al., 2002; Shin, 2017; Linden, 2018) as both raw area [equation 6.8] and percentage [equation 6.9].

$$\hat{IE}_{\tau} = \hat{y}^{post}_{\tau} - \hat{y}^{pre}_{\tau} / \hat{y}^{pre}_{\tau} \qquad \text{for} \quad \tau = t_{+28}...t_{+47} \tag{6.8}$$

$$\hat{IE}_{\tau} = (\hat{y}_{\tau}^{post} - \hat{y}_{\tau}^{pre}/\hat{y}_{\tau}^{pre})100 \qquad \text{for} \quad \tau = t_{+28}...t_{+47} \tag{6.9}$$

In each equation $\hat{IE}$ represents the intervention effect, $\hat{y}_{\tau}^{post}$ should be understood as the *post-policy* modelled data and $\hat{y}_{\tau}^{pre}$ the upper boundary of the counterfactual prediction interval.

In order to allow for a coherent and interpretable result for the cumulative *post-policy* period, a single overall effect was computed based upon the mean of the intervention effects reported for times $t_{+28}, t_{+29}, ...t_{+47}$ [equation 6.10].

$$\hat{IE}_{tot} = (\sum_{i=28}^{48} \hat{IE}_i)/20 \tag{6.10}$$

In the above $\hat{IE}_{tot}$ is the overall intervention effect derived for the entire *post-policy* period and $\hat{IE}_i$ reflects the individual intervention effects at times $t_{+28}, t_{+29}, ...t_{+48}$.

All results were computed using base functions within the *R* (R Core Team, 2019) framework.

6.4 Results

6.4.1 Green Belt at the Time of the Occurrence of Change

Core results derived from the *Interrupted Time Series* analysis are reproduced in **table 6.4**. The analysis estimated a mean area of green space within the 'Green Belt' ***26.39%*** larger than anticipated under the continuation of the previous policy regime. This effect could be considered to equate to an additional **4.97 Ha** of green space being lost per quarter during the *post-policy* period.

Quarter	Absolute Difference Modelled Data (Maximum 95% CI) (m²/Ha)	Percentage Difference (Maximum 95% CI)	Absolute Difference Observed Data (Maximum 95% CI) (m²/Ha)	Percentage Difference (Maximum 95% CI)
Q1 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2014	**0.54**	***59.02%***	2.54	*277.18%*
Q4 2014	**0.20**	***22.02%***	0.00	*0.00%*
Q1 2015	**0.12**	***12.86%***	0.00	*0.00%*
Q2 2015	**0.92**	***97.30%***	4.95	*524.95%*
Q3 2015	**0.67**	***70.03%***	0.00	*0.00%*
Q4 2015	**0.50**	***51.79%***	0.00	*0.00%*
Q1 2016	**0.34**	***35.22%***	0.00	*0.00%*
Q2 2016	**0.28**	***28.54%***	0.00	*0.00%*
Q3 2016	**0.18**	***18.67%***	0.00	*0.00%*
Q4 2016	**0.14**	***13.94%***	0.00	*0.00%*
Q1 2017	**0.22**	***22.24%***	1.34	*133.23%*
Q2 2017	**0.14**	***13.45%***	0.00	*0.00%*
Q3 2017	**0.26**	***25.50%***	2.11	*206.98%*
Q4 2017	**0.19**	***18.85%***	0.00	*0.00%*
Q1 2018	**0.12**	***11.49%***	0.00	*0.00%*
Q2 2018	**0.07**	***6.74%***	0.00	*0.00%*
Q3 2018	**0.13**	***12.35%***	1.35	*128.03%*
Q4 2018	**0.08**	***7.87%***	0.00	*0.00%*

Table 6.4: Estimated Intervention effect representing difference between *post-policy* period and maximum predicted counterfactual boundary (95% Prediction Interval).

The modelled *pre-policy* period evidenced a slightly declining trend in the area of green space undergoing development, potentially associated with economic drivers (Tatliyer, 2017).

Whilst the majority of observations in the *post-policy* period (75%) fell within the prediction interval, the trend modelled by the *dynamic linear model* evidenced additional development more consistently. This effect can be considered to represent an affectation associated with the nature of development, which will not occur constantly, therefore there will necessarily exist significant peaks, which contribute to a more general trend.

The largest single quarter increase (based upon both the modelled and observed data) occurred in quarter 2 of 2015, in which the intervention effect was estimated as an increase of *97.30%*. This can be understood as part of a broader trend, in which the first ten quarters of the *post-policy* period (quarter 1 2014 to quarter 2 2016) were characterised by an average intervention effect of *37.32%*, whereas in the subsequent ten it was just *15.11%*. This effect could be interpreted as suggestive of the intervention leading to increased development in its early stages, which subsequently diminished and plateaued [figure 6.11].

Where based upon observed data the average intervention effect increased significantly to *63.52%* per quarter. However, a little under half of this effect was attributable to the occurrence of a single large developmental quarter discussed previously (quarter 2 of 2015).

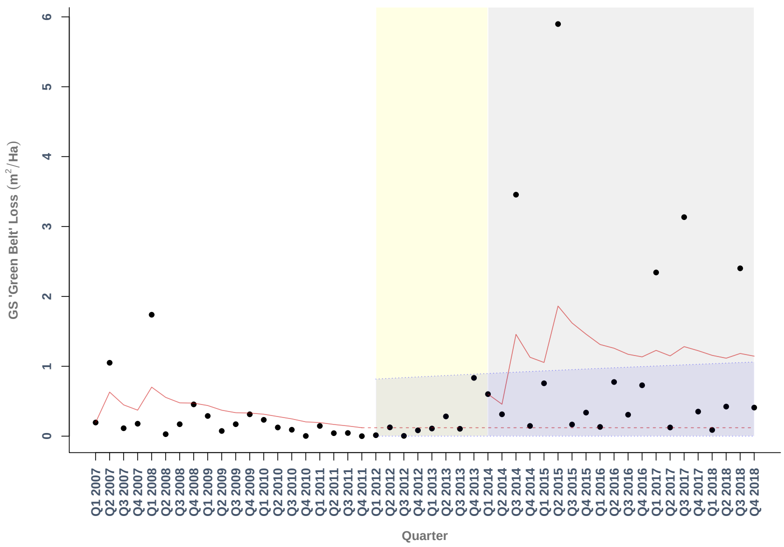

Figure 6.11: Graphical representation of ITS Analysis relating to rates of development within land considered to be 'Green Belt' at the time of change.

When converted to reflect the area within the 'Green Belt' as a proportion of the total recorded development on green space the results become more interesting. The modelled *post-policy* period is mostly within the bounds of the prediction interval throughout. Only in regards to quarters 2 and 3 of 2015 did the modelled *post-policy* data exceed the counterfactual scenario, suggesting per quarter during the *post-policy* period, the intervention effect could be estimated as a *1.12%* increase in area [figure 6.12].

However, the observed data retained five instances in which the proportion of development exceeded the counterfactual, resulting in an estimated intervention effect of *20.10%* per quarter. Over half of this intervention effect was attributable to development which occurred in a single quarter (quarter 2 of 2015) and appears incongruous with general trends. Where this data was excluded from analysis the intervention effect reduced to *8.67%*.

The outlined results can be considered to indicate as a proportion of development levels had not altered significantly between the two periods.

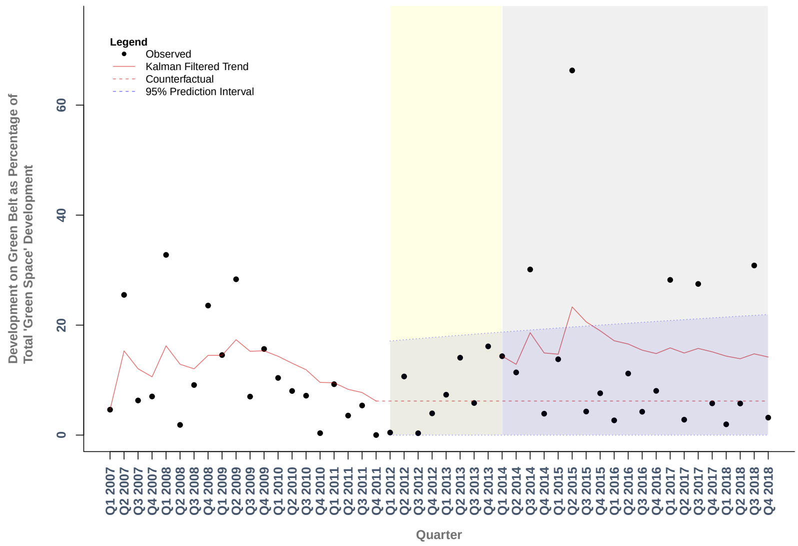

Figure 6.12: Graphical representation of ITS Analysis of the development within the 'Green Belt' as a proportion of total green space development.

6.4.2 Green Belt at any Point Prior to the Occurrence of Change

When updated to include development which occurred upon land from which the 'Green Belt' designation was previously removed, the reported intervention effect, based upon a modelled *post-policy* period, was a ***29.96%*** (**0.29m^2/Ha**) increase in area per quarter. This translated to an average area of green space **5.56 Ha** larger than would have been developed under the prior framework.

It also reflected a slight increase (3.57%) upon the previous 'Green Belt' analysis, which it can be speculated may relate to the increased area of land from which the designation was removed in the *post-policy* period (CPRE, 2018).

Quarter	Absolute Difference Modelled Data (Maximum 95% CI) (m²/Ha)	Percentage Difference (Maximum 95% CI)	Absolute Difference Observed Data (Maximum 95% CI) (m²/Ha)	Percentage Difference (Maximum 95% CI)
Q1 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2014	**0.53**	***57.52%***	2.53	*273.64%*
Q4 2014	**0.20**	***21.47%***	0.00	*0.00%*
Q1 2015	**0.12**	***12.88%***	0.00	*0.00%*
Q2 2015	**0.92**	***98.26%***	4.96	*527.99%*
Q3 2015	**0.68**	***71.62%***	0.00	*0.00%*
Q4 2015	**0.51**	***53.88%***	0.00	*0.00%*
Q1 2016	**0.36**	***37.67%***	0.00	*0.00%*
Q2 2016	**0.30**	***31.41%***	0.00	*0.00%*
Q3 2016	**0.21**	***21.80%***	0.00	*0.00%*
Q4 2016	**0.17**	***17.41%***	0.00	*0.00%*
Q1 2017	**0.26**	***26.44%***	1.37	*141.23%*
Q2 2017	**0.17**	***17.78%***	0.00	*0.00%*
Q3 2017	**0.33**	***33.41%***	2.54	*259.64%*
Q4 2017	**0.26**	***26.75%***	0.00	*0.00%*
Q1 2018	**0.19**	***19.30%***	0.00	*0.00%*
Q2 2018	**0.14**	***14.55%***	0.00	*0.00%*
Q3 2018	**0.21**	***20.73%***	1.40	*140.83%*
Q4 2018	**0.16**	***16.24%***	0.00	*0.00%*

Table 6.5: Estimated intervention effect representing rates of development on land which had been designated as 'Green Belt' at any time.

The maximum intervention effect was recorded as *98.26%* in regards to quarter 2 of 2015. Between quarters 1 of 2014 and 2 of 2016 the average intervention effect was *38.47%*. Whilst in the subsequent period (quarters 3 of 2016 to 4 of 2018) it had declined to *21.44%*. Accordingly, the declining trend evidenced in the second half of the *post-policy* period was less acute than the equivalent derived for loss upon land where 'Green Belt' designation remained in place [figure 6.13].

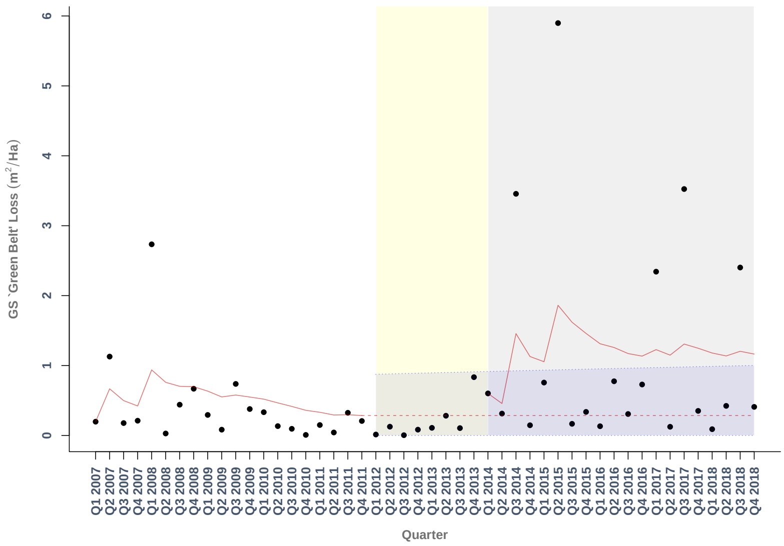

Figure 6.13: Occurrence of development upon green space within land designated as 'Green Belt' at any point prior to the change.

As a proportion of total development upon green space, the area of 'Green Belt' development modelled for the *post-policy* period adhered to the predicted counterfactual throughout. Therefore, no change could be inferred as a result of the revised policy framework. It is noted, a single observation remained outside of the counterfactual interval, reflecting an average intervention effect of *4.82%*. However, this could potentially be interpreted as an anomaly due to its significant deviation from the general trend [figure 6.14].

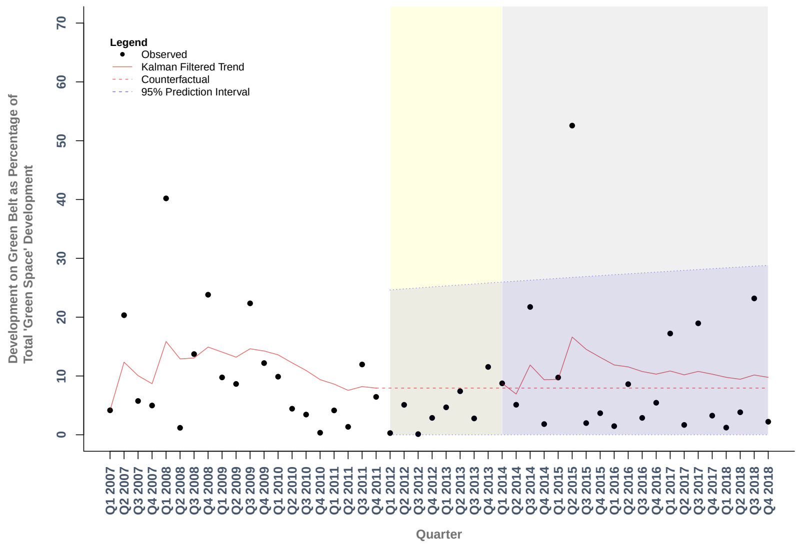

Figure 6.14: Graphical representation of ITS Analysis of the development within the 'Green Belt' as a proportion of total green space development, based upon land designated as 'Green Belt' at any point prior to the occurrence of change.

The two data sets reflected broadly similar patterns, with the modelled data in each showing the area of 'Green Belt' subject to development in the *post-policy* period as between **26%** and **29%** greater than would have been anticipated based upon no intervention having taken place. However, as a proportion of total green space development there was not sufficient evidence to suggest a change had occurred. This could imply under the revised policy framework additional developmental pressure on green space within the 'Green Belt' is more likely attributable to an increased overall rate of development than an explicit diminution in the legal protection afforded to such.

6.4.3 Urban and Rural Change

Results presented within this section of research reflect separately the area of green space loss which occurred outside of the urban boundary, the area of green space which occurred inside the urban boundary and the the area of '*brownfield loss*' which occurred inside the urban boundary. Together they are used to form a picture of the structure of development.

Analysis of rates of development both within and outside of the defined indicative urban boundaries reported significantly different intervention effects.

Quarter	Absolute Difference Modelled Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)	Absolute Difference Observed Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)
Q1 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2017	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2017	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2017	**0.00**	***0.00%***	2.18	*6.36%*
Q4 2017	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2018	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2018	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2018	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2018	**0.00**	***0.00%***	0.00	*0.00%*

Table 6.6: Estimated intervention effect representing rates of development on green space land contained within existing urban boundaries.

The area of development on green space land within the urban boundary was consistent with the prediction derived from the previous policy regime, with no overall effect noted. The modelled *post-policy* period was recorded as being within the prediction boundary in each quarter, whilst only one observation exceeded the counterfactual [figure 6.15]. Although there was a slight trend towards increased development within the *post-policy* period (**0.13m^2/Ha per quarter**), it could not be excluded such was related to external influences (such as economic circumstances).

A single observation was recorded as exceeding the counterfactual prediction interval (quarter 3 of 2017), but could not be considered to represent the general developmental trend. Of the five quarters in which the largest area of green space loss was recorded, three occurred within the *pre-policy* period. Although the largest single area loss was recorded in quarter 3 of 2017.

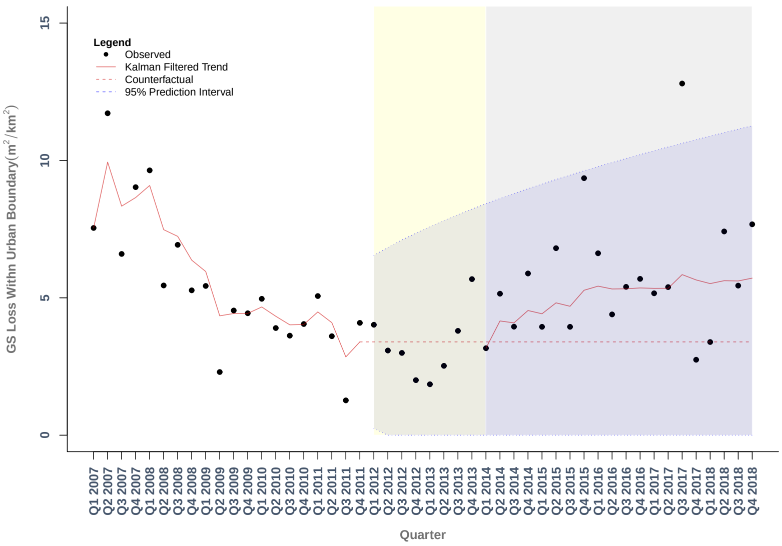

Figure 6.15: DLM Modelled ITS analysis of green space inside the indicative urban boundary

The results presented in **table** 6.7 show the intervention effects recorded in relation to the area of ‘brownfield’ land situated within the urban boundary, which underwent development.

Quarter	Absolute Difference Modelled Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)	Absolute Difference Observed Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)
Q1 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2014	**0.00**	***0.00%***	0.11	*1.68%*
Q3 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2014	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2015	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2016	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2017	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2017	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2017	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2017	**0.00**	***0.00%***	0.00	*0.00%*
Q1 2018	**0.00**	***0.00%***	0.00	*0.00%*
Q2 2018	**0.00**	***0.00%***	0.00	*0.00%*
Q3 2018	**0.00**	***0.00%***	0.00	*0.00%*
Q4 2018	**0.00**	***0.00%***	0.00	*0.00%*

Table 6.7: Estimated intervention effect representing rates of development on ’brownfield’ land contained within existing urban boundaries.

The area of development to occur upon indicative 'brownfield' land during the *post-policy* period also registered no intervention effect. In regards to every quarter the modelled *post-policy* period was wholly contained within the prediction interval associated with the counterfactual scenario [figure 6.16]. The area which underwent development during the *pre-policy* period evidenced a generally declining trend. Between quarter 1 of 2007 and quarter 4 of 2011 it reduced by an average of 2.52 m^2/Ha per quarter.

A decreasing trend was also modelled in the *post-policy* period (0.20m^2/Ha), with a single observation reflecting a *1.69%* positive intervention effect in quarter 2 of 2014. Both the green space and indicative 'brownfield change' data evidenced the policy change to have had a negligible impact upon the area undergoing development.

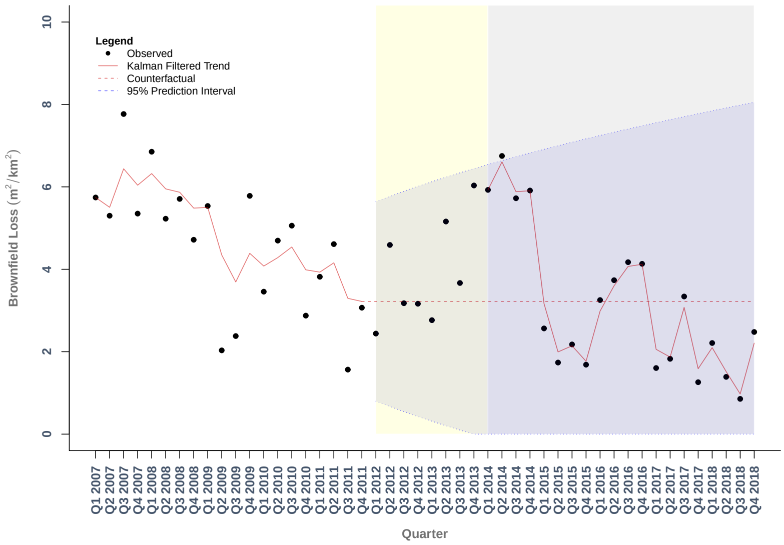

Figure 6.16: DLM Modelled ITS analysis of '*brownfield change*' inside the indicative urban boundary.

Quarter	Absolute Difference Modelled Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)	Absolute Difference Observed Data (Maximum 95% CI) (m^2/Ha)	Percentage Difference (Maximum 95% CI)
Q1 2014	**0.34**	***102.63%***	0.34	*102.63%*
Q2 2014	**0.26**	***78.97%***	0.18	*55.88%*
Q3 2014	**0.63**	***191.89%***	1.33	*404.46%*
Q4 2014	**0.56**	***170.64%***	0.37	*113.5%*
Q1 2015	**0.53**	***160.21%***	0.41	*124.98%*
Q2 2015	**0.56**	***170.92%***	0.70	*213.17%*
Q3 2015	**0.55**	***166.25%***	0.48	*145.73%*
Q4 2015	**0.52**	***157.52%***	0.38	*116.00%*
Q1 2016	**0.51**	***154.47%***	0.46	*139.11%*
Q2 2016	**0.51**	***155.79%***	0.54	*162.74%*
Q3 2016	**0.54**	***164.24%***	0.69	*209.82%*
Q4 2016	**0.61**	***185.04%***	0.99	*299.69%*
Q1 2017	**0.67**	***204.39%***	1.03	*312.77%*
Q2 2017	**0.62**	***188.48%***	0.32	*98.34%*
Q3 2017	**0.73**	***220.51%***	1.33	*403.45%*
Q4 2017	**0.74**	***223.70%***	0.80	*241.99%*
Q1 2018	**0.69**	***208.01%***	0.39	*117.49%*
Q2 2018	**0.68**	***207.04%***	0.66	*201.44%*
Q3 2018	**0.68**	***205.79%***	0.65	*198.50%*
Q4 2018	**0.80**	***241.84%***	1.49	*451.35%*

Table 6.8: Estimated intervention effect representing rates of development on green space land located outside of existing urban boundaries.

In stark contrast, green space loss outside said boundary estimated an additional area of ***177.92%*** (**0.59m^2/Ha**) per quarter to have been the subject of development since the implementation of the revised framework. Across the sample Local Authority Areas an average area of **100.62 Ha** per quarter greater than would have been anticipated under the previous policy was the subject of development [figure 6.17].

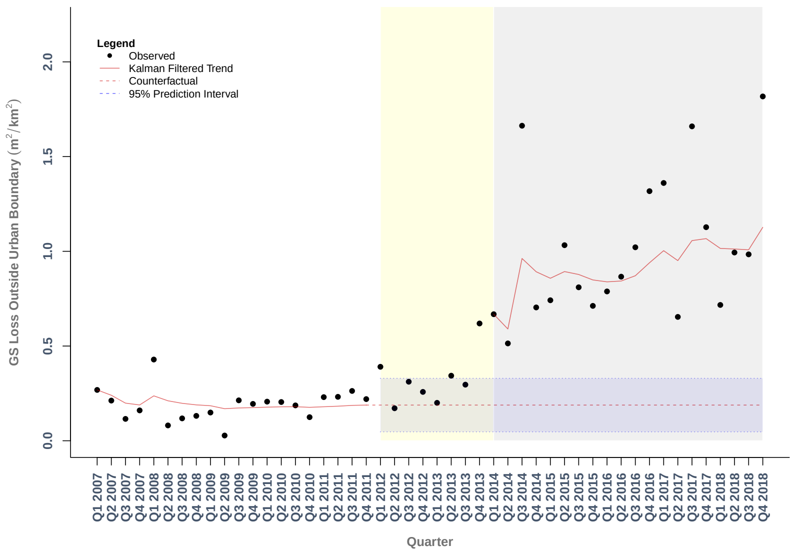

Figure 6.17: DLM Modelled ITS analysis of '*green space loss*' outside of the indicative urban boundary

Results also evidenced an increasing trend in the area of development, culminating in the highest single quarter intervention effect of *241.84%* in relation to quarter 4 or 2018. With the smallest intervention effect having occurred in quarter 2 of 2014 (*78.97%*). Between quarter 1 of 2014 and quarter 2 of 2016 the average intervention effect was estimated as a *150.93%* increase in the occurrence of development on green space, whereas in the remaining period from quarter 3 of 2016 to quarter 4 of 2018 it was recorded as *204.90%*.

Quarter	Intervention Effect 'Green Space Loss' Within Urban Boundary (%)	Intervention Effect 'Brownfield Change' Within Urban Boundary (%)	Intervention Effect 'Green Space Loss' Outside of Urban Boundary (%)
Q1 2014	*0.00%*	*0.00%*	*102.63%*
Q2 2014	*0.00%*	*0.00%*	*78.97%*
Q3 2014	*0.00%*	*0.00%*	*191.89%*
Q4 2014	*0.00%*	*0.00%*	*170.64%*
Q1 2015	*0.00%*	*0.00%*	*160.21%*
Q2 2015	*0.00%*	*0.00%*	*170.92%*
Q3 2015	*0.00%*	*0.00%*	*166.25%*
Q4 2015	*0.00%*	*0.00%*	*157.52%*
Q1 2016	*0.00%*	*0.00%*	*154.47%*
Q2 2016	*0.00%*	*0.00%*	*155.79%*
Q3 2016	*0.00%*	*0.00%*	*164.24%*
Q4 2016	*0.00%*	*0.00%*	*185.04%*
Q1 2017	*0.00%*	*0.00%*	*204.39%*
Q2 2017	*0.00%*	*0.00%*	*188.48%*
Q3 2017	*0.00%*	*0.00%*	*220.51%*
Q4 2017	*0.00%*	*0.00%*	*223.70%*
Q1 2018	*0.00%*	*0.00%*	*208.01%*
Q2 2018	*0.00%*	*0.00%*	*207.04%*
Q3 2018	*0.00%*	*0.00%*	*205.79%*
Q4 2018	*0.00%*	*0.00%*	*241.84%*

Table 6.9: Table showing combined estimated intervention effects for areas of green space and '*brownfield change*' within and green space outside of the indicative urban boundary.

A significantly increased area of green space located outside of existing urban boundaries was evidenced to have been subject to development than would have been anticipated based upon the extrapolation of the general trend under the prior regime. Conversely, both green space and 'brownfield' development contained within the urban boundary showed a negligible intervention effect.

6.5 Discussion

In **Chapter 5** evidence was presented in the form of an estimated intervention effect, which suggested the *post-policy* period had been defined by development upon green space in excess of that which would have been anticipated under the previous framework. The extent to which this could be ascribed to the *Localism Act 2011* and *National Planning Policy Framework* actively enabling development to encroach into previously unaffected rural land at the fringes of urban conurbations (Harrison and Clifford, 2016) had not been assessed quantitatively in an academic context.

With much of the controversy associated with the *Localism Act 2011* and

National Planning Policy Framework relating to its purported threat to protected 'Green Belts' and rural fringe land, this element of research was designed to address the extent to which it could be deemed to have increased urban expansion. The containment of urban areas represents one of the core concerns for policy-makers and land change scientists (European Commission, 2016).

Research Question 3: Do analyses of rates of development upon green space offer insight in regards to the extent to which the revised planning framework can be characterised as enabling urban expansion?

6.5.1 Key Findings

6.5.2 Green Belt Change

The limited direct analysis of rates of development on green space land within designated 'Green Belt' under the terms of the revised planning framework has depicted an increasing rate of loss (CPRE, 2018). In conjunction with evidence of a higher number of applications to develop upon 'Green Belt' (Glenigan, 2018) and the release of a greater area of land than during the majority of years under the previous policy regime (CPRE, 2018), the *Localism Act 2011* and *National Planning Policy Framework* have been characterised as leading to the erosion of vital rural land (Sibley-Esposito, 2014). A contention was posited in regards to whether such could be attributed to a shift in tone towards developmental sprawl or the explicit weakening of protections afforded to 'Green Belt' (Sibley-Esposito, 2014; CPRE, 2018).

In regards to each of the prior analyses (referred to above), stated policy effects were based upon direct comparison of single figures recorded in the *pre-* and *post-policy* periods (broadly reflecting a *pretest-posttest* approach) or reported the *post-policy* trend alone (CPRE, 2018). By applying an *Interrupted Time Series* approach as a means through which to address the attribution problem (Morrison and Pearce, 2000) this research offered robust corroboration of the policy having led to an increase in the rate of development within 'Green Belt'.

However, it should be noted the reported effect associated with the revised planning framework was substantially lower than the relative loss previously outlined. Furthermore, the *post-policy* model evidenced substantive peaks prior to quarter 3 of 2015, but appeared to reduce in effect to a relatively static level thereafter, in direct contrast with the increasing trend reported by CPRE (2018). It can be contended this disparity could be a direct consequence of the differing methodological approaches adopted. The most prominent feature amongst which, was the sample of twenty-two Authorities, which should be compared with national data with some degree of caution in light of the large differences between local rates of development (Dallimer et al., 2011).

It could alternatively relate to the use of a robust counterfactual based quantitative methodology, capable of accounting for trends associated with the previous policy framework (Morrison and Pearce, 2000). Whilst, the *dynamic linear model* based approach to *Interrupted Time Series* analysis was shown to account for variance associated with the influence of economic fluctuation it may conversely have resulted in an overestimated prediction interval, thus reducing the estimated effect.

Interestingly, the results presented in this research evidenced that as a proportion of total development occurring on green space, the loss of 'Green Belt' land within the *post-policy* period broadly adhered to predicted rates under the previous regime. It could be inferred from such, any additional development within the designated 'Green Belt' should be attributed to an increase in total development rather than the diminution of relevant protection afforded in policy. This view to some extent substantiates assertions that provisions within the *NPPF* reflected the continuation of previous protections (Slade, 2018) and could be deemed to suggest additional loss may be more attributable to an overall shift in tone, adopting de-regulation as a means by which to engender free market growth (Sibley-Esposito, 2014).

The effectiveness of 'Green Belt' and similar policies (such as the 'Green Heart' in the Netherlands (Kasraian et al., 2019)) in containing development has been evidenced previously (Bengston and Youn, 2006b; Morrison and Pearce, 2000). However, their efficacy is considered to be associated with combined measures, such as 'brownfield' land targets (Baing, 2010). If it is accepted that 'Green Belt' provisions remained broadly consistent, the recorded increase in the occurrence of development on such land may indicate the influence of a reduction in other policy constraints.

The most prominent alteration between the *NPPF* and its predecessor in relation to 'Green Belt' policy [*PPG2* (DCLG, 2006)] relates to the clarity of definition around the "*very special circumstances*" in which development should be permitted. There is evidence to suggest that decision-makers interpreted elements of the policy in such a way that it led to insufficient protection being afforded to designated land (Sibley-Esposito, 2014). Therefore, it may be speculated that the initial increase followed by subsequent declining trend within the *post-policy* period relate to the evolution of policy through clarification and case law (Cullingworth and Nadin, 2003).

Evidence of increased development within the 'Green Belt' during a short time period does not strictly adhere to established theory around the persistent effects of regulatory provisions, which imply that they continue to restrain development even after abolition (Kasraian et al., 2019). However, the highly responsive nature of the UK system may account for this disparity (Dallimer et al., 2011). Whilst no previous analysis has been undertaken on the transition from a strong regulatory system to a more permissive equivalent (Kasraian et al., 2019). It is in this regards where the *Localism Act 2011* and *NPPF* operating within the a discretionary system offer novel insight.

However, 'Green Belt' policies cannot be considered exclusively from the cultural context, which they have acquired since inception (Gant et al., 2011). Nor extricated from the political cache they hold through prominent lobby representation (Rootes, 2009).

6.5.3 Urban and Rural Change

The results presented in regards to the 42 sample Local Authority Areas evidence materially different intervention effects in regards to development within and outside of indicative urban boundaries. Development upon both green space and '*brownfield*' sites within urban boundaries were consistently in line with the forecast counterfactual, representing the continuation of the previous policy regime. Whilst a single observation in the green space data suggested the *post-policy* period reflected increased development, the modelled data, which should be considered to account for uncertainties, was wholly within the prediction interval. The *post-policy* data did suggest an increasing trend in the area of development on land within the urban boundary, but such appears more likely to be attributable to economic circumstance than directly linked to the policy change.

However, strong evidence was presented of a significant change (*173%*) in the area of green space subject to development in the fringe rural areas surrounding existing urban boundaries. Such findings provide a basis upon which to suggest the revised policy framework did actively enable urban expansion to an extent the preceding framework did not. Allied with the depiction of a declining trend in rates of development upon 'brownfield' sites, it can be hypothesised the effects may be attributable to the weakening of the prior 'brownfield' priority.

As previously stated, the effect of 'brownfield' development targets in protecting 'greenfield' sites had been established in prior research. Although mostly founded upon assessments of secondary, governmental data sources (Baing, 2010; Ganser and Williams, 2007; Ganser, 2008), the restriction of development from encroaching into rural areas was evidenced in satellite imagery (Dallimer et al., 2011). In analysing policy reform, which included the removal of this target, the increased rate of development within the rural fringe can be interpreted as supportive of the efficacy of 'brownfield first' approaches in this regard.

Antecedent studies have primarily based inference of the relationship between land loss associated with urban expansion and policy upon the binary presence or absence of regulatory functions (Colantoni et al., 2016; Fiorini et al., 2019; Kasraian et al., 2019). The outlined results intimate as to a more nuanced relationship, with minimal diminution of protections correlated with a significant effect. Whether such is attributable to the actual terms of the amended provisions or merely perceptions of tonal shift (Sibley-Esposito, 2014) require further investigation.

There is evidence that policies aimed at containment can cause negative effects, including increased pressure upon '*green spaces*' within urban boundaries (Dallimer et al., 2011) and inflated land prices (Cheshire, 2013). The former issue appears not to have been redressed through the implemented reforms as rates of green space loss within the urban boundary remained consistent with that which would have been predicted based upon the prior regime. Crucially, there was evidence to suggest it may have reduced the extent of development upon 'brownfield' sites.

One implication of this combined effect, allied with prior research (Baing, 2010; Ganser and Williams, 2007; Ganser, 2008), is that policy-makers could consider the adoption of similar 'brownfield' targets as a strong measure through which to influence the containment of urban expansion globally.

It is broadly accepted that uncontrolled development favours patterns of urban expansion (Fiorini et al., 2019), with socio-economic trends and governmental planning theorised as the two primary causes of such (Dieleman and Wegener, 2004). Although Dieleman and Wegener (2004) suggested the crucial tier of governance related to regional and local administration, this research presents strong evidence that national changes can induce similar effects.

In 2011 Dallimer et al. (2011) evidenced that a policy of densification had placed pressure upon green space within urban boundaries. It was also intimated that the policy reforms studied in this research (in draft at the time) would likely reverse this effect. The results outlined seem to corroborate this hypothesis, which can be considered to relate to the conceptualisation of policy as a strong function driving and regulating land change.

This research elucidates upon the role of policy measures intended to contain development as a regulator of other social and economic drivers (Bürgi et al., 2005; Hersperger et al., 2018). Morancho (2003) reported that for every additional 100m between a house and green space the value dropped by €1,800. Therefore, areas with abundant green space may be considered likely to maximise developmental revenue. With both physical limitations and prohibitive costs associated with the provision of such within existing boundaries, the rural fringe can be considered at higher risk.

6.5.4 Strengths and Limitations

Through the use of novel data, which allows for the identification of small scale changes to land use within the rural fringe (Smith et al., 2007), allied to analytical methods that synthesise a counterfactual alternative under the prior framework this research constitutes the first to address significant issues identified as crucial to the development of improved understanding of policy as a driver of patterns of land change (Plieninger et al., 2016).

Whilst remote sensed data has been proven to be successful in recording general patterns of development (including large scale urban expansion) (Mu et al., 2016), the detection of small scale incursions into previously undeveloped land at the edge of existing urban conurbations may be improved by data with greater granularity.

Unlike satellite based alternatives the pre-classified data used in this research contained land use detail, which enabled land with differing status within planning policy to be estimated. Whilst the *Interrupted Time Series* analysis methodology provides a more robust estimation of the degree of change which may be attributable to the policy (Morrison and Pearce, 2000; Bernal et al., 2017).

However, the inconsistency in spatial scales between the green space data and relevant urban boundaries (ONS, 2013) may represent a threat to the validity of these results. Due to the 50m resolution of the urban area data, in some cases existing development may exceed the boundary (ONS, 2013), with proximate land change subsequently reflecting a false rural fringe. Whilst considered a genuine concern, the extent to which this could invalidate the results is largely addressed through the application of the same boundaries throughout, meaning that the patterns of change must be deemed consistent. Furthermore, the same boundary data has been utilised in prior research (Dallimer et al., 2011) and was considered adequate in regards to such.

A related issue is identified in regards to the temporal consistency between land change and boundary data. The urban boundary applied in regards to the *pre-policy* period was published in 2001 (UK Data Service, 2018) (6 years prior to the start of the research period). Therefore, development could have expanded urban areas within the intervening period, resulting in an under-estimation of said boundary in 2007. The *post-policy* equivalent related to 2011 (3 years prior to the first recorded *post-policy* data) and may be subject to a corresponding effect. Should this have transpired, the rates of '*green space loss*' to have occurred outside of relevant boundaries would account for a larger area than in actuality. Similarly to the previously discussed issue, this is assessed as unlikely to materially alter the outcome of the research as a result of the reliance upon trends derived from aggregated data based upon a robust sample and the application of prediction intervals (Lin et al., 2018).

By considering three types of data (internal urban green space, external rural green space and 'brownfield' sites) the *ITS* method included a measure of control (Cruz et al., 2017). It would be anticipated that each development type would be subject to the same external forces (such as economic drivers), therefore the differing effects can more confidently be attributed to the policy.

Interestingly, where governmental records related to 'brownfield' development must be understood within the context of different definitions of such land adopted under different policies (Sinnett et al., 2014), the consistent measures adopted in this research could be contended to offer more robust inference.

Due to the relatively small sample of Authorities used in relation to 'Green Belt' data, results can be disproportionately influenced by single instances of large development. Of the total area of **1146978m**^{2}, which underwent change in quarter 2 of 2015, **1143084m**^{2} (*99.66%*) related to a the development of a single site, inland freight facility in Doncaster (Doncaster Council, 2011). However, the proposal was originally approved in August 2011 (prior to the implementation of the revised policy framework) and highlights one of the most significant concerns around the analysis. Instances such as this appear to be limited, but must be considered of high risk, particularly where reporting observed data rather than trend modelled equivalents.

There also exists a concern that without a subset of Local Authority specific data, the reported effect could be biased by large scale development in regards to those with particular profiles. For example, if the evidenced loss of land outside of urban boundaries was heavily concentrated in 'rural' authorities and the decreasing 'brownfield' development was respectively recorded in regards to 'urban' equivalents a different dynamic is emphasised.

Similarly to previous chapters the *ITS* approach builds a predicted counterfactual based upon the extrapolation of patterns of data derived during the pre-policy period and should therefore be considered robust. However, were the model considered to have overfit the data the prediction interval may be unreliable (Greenwood and Matyas, 1990). This issue was primarily addressed throughout with the adoption of prediction intervals, allowing for a range of uncertainty within the *post-policy* period.

The use of aggregated data has precedence in similar research (Dallimer et al., 2011) and due to the robustness of the sample reduces the scope for bias. However, the influence of local and regional variation (evidenced in prior studies (Dallimer et al., 2011)) was not addressed in this research. Due to the highly localised administration of planning within England (Bruton and Nicholson, 2013), it would be interesting to explore the differences encountered in regards to Local Authority Areas. This concept could be investigated using the data profile developed for this research, but was outside of the initial scope.

Analogously, with the quality and types of green space recognised as more influential than area (Wood et al., 2018) the development of analysis incorporating consistent land use should be undertaken to advance the field further.

6.5.5 Implications

The rate of development which occurs upon rural land situated outside of existing urban boundaries appears to be influenced by national planning provisions, although filtered through local governance structures. With similar effects evidenced in regards to a 'zoning' based system within China (Mu et al., 2016), it hints towards a universal relationship. This view is to some extent challenged by Dieleman and Wegener (2004) whom reported regional tiers to play a significant role in urban containment.

Evidence that green space loss within the 'Green Belt', as a proportion of total loss, adhered to the predicted range based upon the prior framework is supportive of both the consistency between policies and potentially alludes to the cultural importance embedded into the identification of land as such (Cheshire, 2013). Having formed a key constituent of planning since inception (Cullingworth and Nadin, 2003), it can be hypothesised there may exist a legacy effect associated with 'Green Belt' similar to the 'Green Heart' conservation policy described in Kasraian et al. (2019).

However, rural land without regulatory protection suffered a dramatic reduction under the revised framework. Based upon prior analysis, which emphasised the key role of 'brownfield' targets in directing development away from rural sites (Ganser and Williams, 2007), the outlined effect is contended to be linked to the weakening of 'brownfield first' policy commitments (Harris, 2012). However, it also must be considered within the context of a general tone supportive of increased rates of development. This concentration of increased development outside of existing urban boundaries may also suggest different types of land loss (primarily agricultural (Colantoni et al., 2016)) and different types of development, reflecting lower densities (Bibby, 2009).

Under the preceding framework, the area of green space within urban boundaries was reported to have diminished relative to the area outside (Dallimer et al., 2011). The subsequent increased loss of land situated outside of urban boundaries under the revised framework, allied with little evidence of reduced rates of green space loss within said boundaries suggests the policy changes have not delivered an improved balance between development and environmental protection. Perhaps reinforcing the view outlined in Barker (2008) that "*there is no getting away from the fact that more undeveloped land will be needed [for development], imposing an environmental cost*". If this is the case there is a need to develop policy procedures to ensure protection is afforded to land based upon robust assessment of its ecosystem services (European Commission, 2016).

6.6 Conclusions

Following the transition to the *Localism Act 2011* and *National Planning Policy Framework* cumulative analysis of rates of development upon green space and 'brownfield' sites suggest a move away from a policy onus upon containment. A significant increase in the occurrence of such upon green space within the rural fringe was evidenced. Whilst increased loss within designated 'Green Belt' also reflected a fundamental change in tone.

Although difficult to report the association between these effects and specific provisions within the policy, there was evidence to suggest changes to 'Green Belt' protections had a less notable impact than those associated with 'brownfield' land. In fact, the limited effect noted in regards to 'Green Belt' development as a proportion of total green space suggested protections had not been significantly diminished.

The role of national planning as a driver and regulator in relation to patterns of land change was supported by the outlined outcomes. Across a sample of diverse localities the cumulative effect was highly likely to be attributable to the national intervention.

With policies intended to constrain urban areas a global priority, the outcome of this research and its inference in regards to the relationship between national level policy and patterns of development adds to existing understanding. Understood within the context of prior research in relation to formal targets for 'brownfield' development (Baing, 2010; Ganser and Williams, 2007; Ganser, 2008) there is evidence to support the efficacy of such as a generalizable approach to development. However, measures must be implemented in conjunction with developmental design, which prioritises the role of green spaces and accessibility (Paterson, 2012).

CHAPTER 7

Discussion

Under pressure of urbanisation, the loss of undeveloped green space to growing cities has evolved as a global priority. The role of policy in the regulation of this process has tacitly been acknowledged, but remains lacking in robust quantitative methods of analysis. This thesis was intended to develop an advanced understanding of the relationship between planning policy and land use, through exploration of effects associated with the transition between two policy frameworks within England.

In order to undertake this aim, three interconnected elements of research were developed to address the following questions.

Research Question 1: Has the area of green space which was subject to development evidenced alteration in rates which could such be associated with the adoption of the *Localism Act 2011* and *National Planning Policy Framework (2012)*?

Research Question 2: What impact have the *Localism Act 2011* and *National Planning Policy Framework* had upon the total area of green space subject to development?

Research Question 3: Do analyses of rates of development upon green space offer insights in regards to the extent to which the revised planning framework can be characterised as enabling urban expansion?

The cumulative contribution of these questions towards understanding of the relationship between national level policy and land change through empirical methods is discussed in the following section.

7.1 Key Findings

Under the provisions of the *Localism Act 2011* and *National Planning Policy Framework* a greater area of green space was lost to urban development than would have been the case under the preceding regime. The vast majority of this loss was concentrated outside of existing urban areas, suggesting a paradigmatic shift towards urban expansion. Although based upon an expanded range of indicators the results largely adhered to the effect presented by the *Campaign to Protect Rural England*, based upon analysis of recorded development and applications to develop within the 'Green Belt' (CPRE, 2018).

Previously, the absence of regulation has been identified as a highly significant factor in enabling patterns of urban sprawl (Colantoni et al., 2016; Fiorini et al., 2019). This was considered to emphasise the power of underlying social, economic and territorial drivers (Colantoni et al., 2016) and leads to a rational inference that regulatory policies are a key tool in the containment of development, advocated by subsequent studies focused upon dedicated approaches to densification (Ganser and Williams, 2007; Hersperger et al., 2018; Kasraian et al., 2019). In tandem with Mu et al. (2016), the outcomes of this thesis relate similar effects to a mere diminution of regulatory function. Semantically, the revised policy framework was largely congruent with its predecessor, intimating that minimal change can result in material shifts to the spatial patterns of development.

As mentioned in **chapter 4** the evidence of changes to both rates and patterns of development in regards to the research indicator challenges existing *a posteriori* understanding of the temporal dynamics, which were assumed to underpin the relationship between policy and land change (Bengston et al., 2004; Kasraian et al., 2019; Morrison and Pearce, 2000; Mu et al., 2016). In relation to two different policies, Kasraian et al. (2019) identified subsequent land change to be influenced within a decade, but reported long term legacy effects in the succeeding decades. The three elements of this thesis all indicate the occurrence of change attributable to the policy within a period of two years. Whether this is consistent with Kasraian et al. (2019) and is solely as a result of the utilisation of a data source obtained at shorter time intervals can be speculated upon. However, it would suggest there is a less discernible legacy effect, which could be attributed to the difference between active 'zoning' policies intended to direct development (Kasraian et al., 2019) and responsive, discretionary policies operated within the United Kingdom (Booth, 1995).

It can be postulated different temporal dynamics would be evidenced between the two systems as a 'zoning' approach would necessarily incur a lag between the allocation of land for development and the beginning of construction. Whereas under an equivalent discretionary system the policy can influence the decisions to approve applications to develop from the date of implementation.

Based upon proportional change in area, Dallimer et al. (2011) reported the planning framework in place between 2001 and 2006 to have resulted in a loss of green space. Therefore, the subsequent increased rate of green space loss reported in this research (based upon a coincident period and policy) indicates a continuing trend in which undeveloped land has been consumed by urbanisation. However, due to methodological differences, including the separation of 'brownfield' sites, this inference must be interpreted with caution.

The outlined findings also offer strong evidence of an association between national level policy and the area of undeveloped green space. In this regards it is concordant with existing literature (Hersperger et al., 2018).

7.2 Overall Contribution

In conjunction the work undertaken throughout this thesis explored the causal relationship between national level policies and the regulation of land change, using novel quantitative methods as a means through which to augment existing conceptual models (Hersperger et al., 2018). Whilst empirical research has formulated a strong foundation for the relative role of policy as an underlying driver of land change (primarily using regression models (Kasraian et al., 2019)) the effect associated with policy change had not been assessed in accordance with counterfactual based, outcome focused, impact models (Morrison and Pearce, 2000). Addressing this with data based upon substantive policy cases can be contended to represent a key element in the advancement of an understanding around the dynamics behind the role of national policy.

Alternative data sources were utilised throughout as a means to address issues associated with the identification and categorisation of relevant urban induced land change (Bürgi et al., 2005; Plieninger et al., 2016). Further enabling the incorporation of small scale development as an indicator. Each analytical chapter expanded existing knowledge in regards to the temporal dynamics associated with national policy (Bürgi et al., 2005), challenging existing preconceptions (Bengston et al., 2004; Kasraian et al., 2019; Mu et al., 2016). Whilst focused upon the effect of changes in regulatory function based upon stable landscapes, which had largely been omitted from prior research (Bürgi et al., 2005; Plieninger et al., 2016).

In so doing, the research represents an apt extension to work undertaken by Dallimer et al. (2011), which evidenced a shift in developmental patterns upon green space to within existing urban boundaries. This effect was attributed to the policy framework which constituted the *pre-policy* period within this thesis. In tandem they offer a strong quantitative foundation through which to inform the mechanisms for policy to balance environmental and developmental needs, identified as a critical aim to global sustainability (Dallimer et al., 2011).

7.3 Implications for Urban Science

Through employing an inter-disciplinary approach based upon foundational concepts of land science, geoinformatics and data analytics, this thesis evidenced how robust statistical techniques utilised widely in other fields of research could offer new insights, addressing some of the methodological challenges raised in regards to the interpretation of planning policy (Morrison and Pearce, 2000). *Change Point Detection* was established as an approach through which to derive understanding of the temporal dynamics of policies. As urban science evolves a plethora of data through which to monitor urban dynamics from individual to population level (Kontokosta, 2018), online *Change Point Detection* could be used to both identify the existence of an effect associated with a policy and provide vital information as to the time frames in which it occurred. Whilst *Interrupted Time Series* analysis using accessible sources of large scale longitudinal data and advanced computational modelling techniques provided a robust estimation of intervention effects. However, to date such policy impact evaluation processes have been lacking in urban science (Daniel, 2017).

The research developed a green space land change dataset combining detailed topographical and functional use resources, which enabled the distinction between green space and 'brownfield' land. Subsequently, spatially joined to openly accessible boundary data, this provided the means to assess relative rates of change and offered potential insight in regards to the identification of provisions within the policy framework.

The work undertaken throughout this thesis also highlights the value of retrospective data-driven, longitudinal studies in support of the advancement of conceptual understanding of the factors influencing urban development. Whilst longitudinal analyses form a core aspect of urban science, in reality such constitute a relatively minimally explored element of research to date (Kitchin, 2016).

In recent years data-driven approaches to urban planning have evolved, including the use of digital models intended to simulate changes to patterns of land use under different policy scenarios (Koomen and Stillwell, 2007). Population dynamics, climatic conditions and economic drivers of growth are well established within these models (Pettit et al., 2020). However, policy scenarios commonly apply relatively binary assumptions based upon regulated constraint of development or largely deregulatory expansion (Dorning et al., 2015; Han et al., 2015; Pettit et al., 2020). This may in part be attributed to a scarcity of data derived from *ex post facto* impact evaluation with which to inform such (Shahab et al., 2019).

The impact upon green space land associated with subtle changes to national level planning policy derived from this research can contribute novel insight in this regard. The two distinct methods (*Change Point Detection* and *Interrupted Time Series* Analysis) used in **chapters 4**, **5** and **6** represent the first application within the context of planning policy. They cumulatively address the identified need to adopt more robust methods around causal inference in regards to planning policy as an underlying driver of land change (Morrison and Pearce, 2000; Plieninger et al., 2016). With the *ITS* approach in particular offering a widely applicable computational system modelling approach through a synthetic counterfactual.

It further emphasises the discord between urban analytics and planning policy practice alluded to by Hersperger et al. (2018), which may be deemed reflective of wider challenges. Where much urban science research implies a potential to influence policy a fracture remains (Thakuriah et al., 2017). By reframing the focus of research from land change processes to the use of land change as data to support an explicit analysis of policy the outlined may move towards advancing a minimally addressed field of research.

7.4 Implications for Planning Policy

This thesis is the first work to present robust empirical evidence that the transition to the *Localism Act 2011* and *National Planning Policy Framework* has resulted in a significantly larger rate of green space loss than would have occurred under its predecessor. Whilst the revised provisions may not have been deemed to reflect a 'radical' reform agenda (Davoudi, 2011; Haughton and Allmendinger, 2013; Raco, 2014), an implicit shift in tone, allied to the weakening of regulatory requirements appears to have induced this effect.

The *National Planning Policy Framework* was originally outlined as intended to "*protect the environment and cultural landscapes*" and support sustainable development (Bolton, 2011) amongst other aims. The evidence of the increased loss of natural land presented in this research would imply it failed to adhere to the outlined objectives in the face of other pressures.

Politically, consideration of contemporary planning policy in the United Kingdom cannot be extricated from the perceived 'housing crisis', which has led successive government's to commit to programmes of increased development (Cheshire, 2013). Thus, the revised framework and its effects must be understood within the context of this divisive issue. Across each year of the *post-policy* period identified by this research (2014 to 2018), the largest recorded number of new residential developments begun nationally within each year was recorded as 166,560 (2018 - 2019), which was **3,880** lower than in 2007 to 2008 (MHCLG, 2020c). This reflects a similar pattern to the research sample and would suggest the additional green space loss incurred under the revised framework has not been offset by the provision of more housing. In light of this evidence it adds support to the contention that the policy reforms merely served to prioritise economic growth at the expense of our environmental future (Tait and Inch, 2016).

The persistence of the trend towards greater green space loss under the revised framework also suggests the policy has potentially led to local plans being forced to commit larger areas of green space for future development (Harris, 2012), which will have had a continuing effect in the years since 2018. Although analysis of the impacts of the 2018 reforms would be necessary it may be considered likely the retention of a generally more permissive tone will mean similar effects are evidenced.

However, the highly responsive dynamic seen in the transition between the prior regime and *National Planning Policy Framework*, allied to similar effects reported by Dallimer et al. (2011) would enable mitigatory reform to respond to this issue more quickly than may have been anticipated.

Both the significant increase in the area of green space loss outside of existing urban boundaries and diminishing trend in development on 'brownfield' land within, suggested targeted policy provisions (such as 'brownfield' first measures) weakened in the revised framework were potentially pivotal (Ganser and Williams, 2007). This has coincided with reports that there is sufficient 'brownfield' land to allow for the development of 1.8 million new homes (CPRE, 2019). In combination with the institution of 'Brownfield Land Registers' (DCLG, 2017), the pre-approval of residential development on such sites could help to alter patterns of development (European Commission, 2016).

Regional factors were previously identified as critical to the containment of development (Dieleman and Wegener, 2004). However, the reported impact confirms Central Government as an influential driving force (Mu et al., 2016). Therefore, suggesting the national planning agenda, as outlined in relevant policy, will be crucial in striking a balance between developmental needs and the retention of environmentally important undeveloped green space (Dallimer et al., 2011). To facilitate a policy both supportive of development and which affords appropriate protection to green space, impact evaluation must be prioritised (Dallimer et al., 2011; Shahab et al., 2019). The highly granular vector data (scale of 1:2500) utilised throughout the research and novel application of previously unused analytical methods offer replicable approaches to address this need.

7.5 Limitations

7.5.1 Limitation 1: Land Change Data Accuracy

Throughout the research a single data source was utilised. Although all measures were taken to ensure the validity of derived land change three issues could be highlighted as potentially limiting. The first relates to the adopted change metric. The second to the external influence of 'land banking'. Whilst the third is associated with issues of temporal accuracy.

Commonly, land change studies compare the total areas recorded as green space at separate time intervals (Dallimer et al., 2011). In addition to which they predominantly only identify change at the completion of development, primarily as a result of identification of change through satellite imagery, in which the transition from green space to pre-developmental ground-work is less easily discerned (Erener and Düzgün, 2009).

However, this research adopted the area of green space which underwent development as a more reliably defined identifier of change within the OS data set. This also included the transition between '*natural*' surfaces and initial ground-works.

Therefore, the data accounted for neither the extent of green space, which would be reinstated following the completion of development (Thomas and Littlewood, 2010) nor 'biodiversity offsetting' (Sibley-Esposito, 2014), in which the environmental functions are compensated for at a replacement site (Sullivan and Hannis, 2015). Furthermore, the provision of well designed green space has become a core component of development, inextricably bound to the maximisation of revenue (Panduro and Veie, 2013). Thus, the extent of green space provision upon redeveloped sites could be significantly higher than recorded. Combined, these factors could be considered to lead to an over-estimate of the policy effect, particularly in light of the *National Planning Policy Framework* formally prescribing a commitment to 'green infrastructure' as a component of local plans, which should;

> *plan positively for the creation, protection, enhancement and management of networks of biodiversity and green infrastructure* (National Planning Policy Framework [s.114]).

The area of green space restored to sites identified as being under development is considered unlikely to have biased the results, as an identical approach was undertaken to the classification of change across the entire research period. Therefore, it would be anticipated that the *pre-policy* and *post-policy* periods would be equally affected. However, the validity of this assumption is predicated upon the accuracy of land cover identification administered through *OS* throughout the research period. There is little evidence to suggest this could have been an issue with both a consistent methodology and update procedure applied since prior to 2007 (Ordnance Survey, 2004).

Were rates of 'biodiversity offsetting' to be evidenced to have changed during the research period it could to some extent bias the outcomes of the research. There is little accessible data with which to assess the number of 'offsetting' schemes undertaken within the UK, therefore making it difficult to address this concern. However, the efficacy and practical applicability of such schemes have been disputed based upon analysis of sites in the United States of America (Taherzadeh and Howley, 2018). With schemes rarely delivering commensurate ecosystem services, particularly in regards to public accessibility.

The second and third issues outlined in regards to the underlying change data set can be considered jointly. Although adopted analytical time frames were informed by prior research (Shelter, 2019) the identification of the date upon which a change was approved was subject to some degree of uncertainty. In one example, a large area of development, which was identified as having occurred in 2015 (under *post-policy* conditions) was actually approved under the prior framework (2011) (Doncaster Council, 2011). The extended time period between approval and development in this instance could be attributed to the site forming part of a regional infrastructure project, with elements subject to procurement processes (Williams, 2013). The influence of approval dates upon the data should be considered a significant issue. However, the consistency offered by the identification methodology and model of general trends should to some extent mitigate against bias associated with this risk.

Further to the outlined, the reliable identification of dates at which recorded change could be associated with approval is potentially confounded by instances of 'land banking', in which developmental approval is obtained, but does not occur (HBF, 2014). Land may be retained until such time as it is financially more beneficial to begin development (Payne et al., 2019), at which point it would be identified as change within the data. Conditions requiring development to begin within defined time frames are intended to address this issue (MHCLG, 2020d), and should generally limit delays between approval and identification within this data set to between 5 and a half (*pre-policy*) and 3 and a half years (*post-policy*). However, the purported prevalence of the technique (Payne et al., 2019) could reduce the identified rates of development in both periods.

Evidence from governmental reviews has suggested the issue is less significant than commonly implied (MHCLG, 2018b) and the practice was shown to have reduced after the 2008 financial crash (Payne et al., 2019). Equally, the issue is of greater concern for housing supply, with the practice only impacting upon the derived data if development was to begin. Allied to the evidence of a defined structural shift in the data, which could only have been induced by a large scale single release of land into the supply, significant bias based upon such appears unlikely.

A final issue related to the identification of change concerned development which occurred in distinct phases over a prolonged period. Where large scale projects are undertaken on complex sites or future capital is structured around initial sales (Lichfields, 2016), land change may occur over multiple time intervals. This could have led to bias within the data if portions of development during the *post-policy* period were associated with phased development approved and initiated in the *pre-policy* period. As the proximity to recent development constitutes a material factor in regards to the location of new sites (Nuissl and Siedentop, 2020) there were no means by which to reliably identify phases of single projects based upon spatial characteristics. However, as with other concerns the existence of significant bias appears unlikely based upon the robust types of analysis undertaken.

7.5.2 Limitation 2: Adopted Policy Indicators

In general, planning policies are intended to address a variety of complex, interdependent aims within a single framework (Bengston and Youn, 2006a). Consequently, the identification of appropriate indicators of effects are considered a conceptual problem (Morrison and Pearce, 2000). The adoption of a simple binary indicator of policy effects (such as green space) is contended to offer a reductive approach, which is ill-equipped to address the complexity inherent to the system (Hersperger et al., 2018). However, single indicator studies have previously been undertaken, with loss of natural land considered to reflect a strong proxy for unintended policy effects (Bengston et al., 2004; Bengston and Youn, 2006a; Dallimer et al., 2011; Elson et al., 1993; Kasraian et al., 2019; Mu et al., 2016).

7.5.3 Limitation 3: Importance of Quality and Area

The research undertaken throughout this thesis assigned equal importance to all forms of green space, conceptualising sustainable development within the context of the '*no net land take*' principle (European Commission, 2016). However, the ecosystem service functions associated with land are recognised as being heavily influenced by quality (Brindley et al., 2019; Wood et al., 2018). Therefore, analyses which envisage space as a neutral concept will fail to account for the nuances crucial to the development of urban forms that meet multi-functional needs (McGuinness et al., 2018).

As a result of the adopted change identification method, the data incorporated small area changes (including incidental spaces (Swanwick et al., 2003)) within aggregated forms, which did not account for indicators of quality (such as ecological richness). This issue can be considered in relation to the UK housing crisis, which has come to redefine planning in the Twenty-First Century. Barker (2008) suggested "*there was no getting away from the fact that more undeveloped land will be needed*". Based upon the understanding that a small area of highly verdant land cover can provide greater ecosystem service functions than a large area of amenity grassland (Brindley et al., 2019), the adoption of spatial planning principles which prioritise the protection and enhancement of some '*green spaces*', whilst enabling sensitive development upon others may be a more beneficial approach. This is recognised as a particular issue in regards to quality accessible urban spaces, which have been shown to come under increased pressure where densification is pursued (Dallimer et al., 2011).

The outlined approach also does not account for the environmental and social value which can bee attributed to 'brownfield' land (Macadam and Bairner, 2012). Particularly from a biodiversity perspective, undeveloped land can provide greater benefits than large scale rural areas dominated by intensively farmed monoculture crops (Hunter, 2014). Further research, building upon this basis may therefore be deemed crucial to build in issues of quality. However, such is difficult to achieve in regards to large sample, temporal analysis based upon historic data (Salkind, 2010).

7.5.4 Limitation 4: Causal Inference

Whilst the *Interrupted Time Series* analysis methodology is designed to offer robust estimation of causal relationships based upon the concept of statistical counterfactual causality (McDowall et al., 2019), it is underpinned by reductive assumptions of linearity (Linden, 2017). As an exploratory approach it is contended to offer strong internal validity (Baicker and Svoronos, 2019) and offer insight of causal association (Young et al., 2014), but in isolation does not adhere to conditions required for causality to be identified (Athey and Imbens, 2017) (particularly in light of the presence of systemic complexity (Trafimow, 2017)).

The method remains vulnerable to inferential challenges. The most commonly cited of which relates to historical bias (Linden, 2017). Within this research potentially confounding events, such as the economic recovery were discussed and attempts were made to account for them accordingly. However, there are limited means by which to exclude the impact of external factors upon the derived inference. In the analysis undertaken in **chapter 6** the differing effects noted in relation to 'brownfield' and green space sites within existing urban boundaries were highly suggestive of policy impact as they would likely have been the subject of similar external factors.

This is a particular issue in regards to the highly complex environment in which planing policy is required to operate (Hersperger et al., 2018). Although the degree of uncertainty built into analysis through the use of *dynamic linear models* and additionality associated with economic normalisation (Morrison and Pearce, 2000) addressed this issue to some extent. The *ITS* method did not explicitly account for complexity and in the absence of a viable control group must therefore be considered subject to potential bias as a result of extraneous variables (Linden, 2017). Post-analytical consideration was given to plausible alternatives for the evidenced effect

(Roemmele et al., 2011), but should not be considered to have addressed the potential for such to be related to a combination of complex, interacting drivers.

This issue is exacerbated by the existence of an extended period between the implementation of the policy and modelling of its effects (Lane and Hall, 2019). Although *a priori* research was used to inform the modelling of this period (Lichfields, 2016; Shelter, 2019), the existence of a significant lagged effect diminishes the derived inference (Galster et al., 2004; Penfold and Zhang, 2013).

The second threat concerns the validity of the *pre-policy* model and thus the extrapolated '*counterfactual*' scenario (Biglan et al., 2000). This issue is highlighted as of particularly concern in regards to highly stochastic data. Throughout the research, *dynamic linear models* were evidenced to be the best fitting approach under formal testing against alternatives. Said models are suited to stochastic data (Brodersen et al., 2015; Brodersen and Hauser, 2020), whilst the number of observations could be considered to mitigate against bias associated with outliers (Zhang et al., 2011). Additionally, the adoption of a functional prediction interval attempted to account for a degree of underlying uncertainty within the structure of the data.

The threat associated with instrumentation (Linden and Yarnold, 2016) was considered minimal throughout. Internal validity can be reduced in circumstances where the methods of data production are subject to change during the research period (Bernal et al., 2017) (such as the methodological change to governmental records on land use change (DCLG, 2015a)). By developing a new land change dataset using the same criteria for each time step, founded upon a consistent revision policy (Ordnance Survey, 2020), derived data was considered unlikely to have resulted in bias.

7.5.5 Limitation 5: Generalisation

A robust sample of Local Authority Areas in England was derived for this thesis, which consequently may be considered likely to reflect national trends. However, analysis at an aggregated scale should be interpreted cautiously in relation to individual local and regional areas, previously evidenced to respond differently to policy influences (Dallimer et al., 2011). This concept was provisionally tested within the research, but requires more detailed analysis of the relationship between local features and the impact of the policy (such as political control, location or economic profile).

Research outcomes must also be understood within the context of the relatively unique context of a discretionary system (Booth, 1995). Despite the system of local plans moving towards an implicit zoning approach (Allmendinger, 2006), formal zoning systems may have evidenced distinct effects under similar deregulatory provisions. Furthermore, the recorded effects may be attributable to interconnected external factors determining the specific provisions of the revised framework. Therefore, the extent to which the research can inform global sustainable development may be limited. However, the work was supportive of prior research undertaken within a global context (Colantoni et al., 2016; Fiorini et al., 2019; Kasraian et al., 2019; Mu et al., 2016) and as such may indicate the role of regulatory functions to be crucial in a variety of contexts.

7.5.6 Limitation 6: Spatial Scale

Due to practical limitations the research could not be conducted at a spatial scale corresponding to the national level of the subject intervention, considered most appropriate (Kozak and Szwagrzyk, 2016). Adhering to the approaches utilised in prior analyses (Dallimer et al., 2011; Kasraian et al., 2019; Mu et al., 2016) it was therefore based upon a sample designed to reflect a broad range of contextual criteria intended to estimate representation of the national scale (Cullingworth and Nadin, 2003). In line with the administration of planning research was aggregated upon Local Authority Areas. Said LAAs were not analysed individually, whilst the spatial scale differed significantly from that which is commonly applied in comparable urban studies (Lloyd, 2016).

Therefore results must be interpreted in relation to the *modifiable areal unit problem* (Openshaw and Rao, 1995). Should the research have been conducted in regards to different spatial scales it could be liable to produce different outcomes. Similarly, a selection of different Local Authority Area samples may lead to a report of a different intervention effect. Particularly in light of more significant correlations being reported at a larger aggregated scale, there is the potential for bias to have been introduced (Lee and Kemp, 2000).

CHAPTER 8

Conclusions and Future Work

8.1 Future Research

The advancement of a reliable conceptual model relating to the role of national level policy as a driver and regulator of land use change requires consistent long term monitoring (OECD, 2018). Allied to Dallimer et al. (2011) this research can provide a basis upon which to extend to future planning policy changes. With comparable analysis of the land change effects associated with the revision of the *NPPF* in 2018 potentially providing insight in regards to the extent to which the outlined effects were attributable to specific provisions or a general shift in tone (Davoudi, 2011).

One of the weaknesses of this research related to the identification of the date upon which development was approved, which could be considered crucial. This issue could be addressed through access to relevant planning application data relating to each sample Local Authority Area and would build upon a growing aspiration to utilise such in support of evidence based decision making (Mills, 2020). Whilst data relating to a small number of sample Authority Areas was accessed and geo-located using RegEx functions based upon postcode pattern matches (Mitchell et al., 2014), future research will be required in order to develop more consistent, replicable methods.

Planning research to date, including this thesis has treated land and land use as a broadly neutral concept (McGuinness et al., 2018). In light of the importance of the characteristics of green spaces to the ecosystem services which can be derived (Brindley et al., 2019; Wood et al., 2018), further research must evolve to incorporate concepts of quality, which have been used previously in regards to analyses of green space accessibility (Barbosa et al., 2007). Such research would provide essential understanding of the effects associated with different policy approaches upon different types of land. The required longitudinal studies for causal inference are commonly restricted by the limited availability of historic data relating to quality (Feltynowski et al., 2018). Therefore, as an initial stage of research there is a need to develop a consistent green space quality database, which could undergo regular revision and is stored in accessible archival format.

Having provided a robust sample as a proof of concept, the extension of the outlined methodology to large scale national data represents a future research priority. It must also be replicated within different contexts, such as in relation to 'zoning' systems (Booth, 1995) and alternative governmental structures in order to ensure understanding of the relationship is advanced.

There is significant scope to extend this research to analyse the degree of variation between individual Local Authorities, in order to develop a model of the influence of regional policy. Based upon the large variation noted by Dallimer et al. (2011), it would be anticipated that similar effects would be evidenced in this context. Subsequent investigation of local development plans would further advise as to optimal approaches for intended outcomes. Machine learning techniques, including *decision tree architecture* and *k-means* clustering could be utilised to explore the relationships between individual Authority characteristics and the extent of green space loss under different policy regimes. However, this endeavour would require a larger sample than was utilised in this research and extensive processing power.

The replication of this research in regards to various subsets of the sample could augment the outlined knowledge, exploring differences between 'urban' and 'rural' Authorities, economic profiles or geographical location. Whilst, the establishment of typologies relating to parcels of green space land, using combined Local Authority, remote sensed and *OS* data, could be used to develop an advanced predictive model for future land use change, building upon work undertaken by amongst others Stanilov and Batty (2011).

There may be value in undertaking research to investigate the extent to which different policy effects are evidenced in regards to green space associated with Local Authority socio-economic profiles. Barbosa et al. (2007) identified that areas characterised by higher deprivation were supported by larger areas of public green space. Whether loss induced by policy has altered this profile could inform the degree of regulatory protection afforded to such spaces under future policy provisions. Similar research could be undertaken based upon the local political profile, such as to investigate whether Authority Areas or Wards served by different political parties saw differing effects. How this links to public participation within the planning system could also be investigated using the outlined methods.

It would be beneficial for research to consider the same policy change and time period, but address the issue using an alternative indicative variable, such as the total number of new residential buildings, number of planning applications or adjusted value of commercial revenue. Finally, there would be value in replicating the analytical methods for data derived from remote sensed sources.

8.1.1 Key Recommendations

Whilst offering novel insights at an aggregated spatial scale, building upon the foundations of Dallimer et al. (2011), the research presented within this thesis does not actively address the vast scope of data to support analysis of local influences. As a result, the following key future research recommendations are outlined.

1. In light of the potentially significant effects upon analysis associated with the adopted spatial scale (Openshaw and Rao, 1995; Wong, 2004; Lloyd, 2016), differential impacts between localities recorded by Dallimer et al. (2011) and influence of local decisions upon planning procedure (Cullingworth and Nadin, 2003), it would appear crucial that research is subsequently undertaken with which to discern the impact of the policy in relation to different areas. An initial approach based upon the data utilised in this thesis proposed the use of *K-means clustering* using the outcomes of individual ITS as a method through which to identify common characteristics between different Local Authority Areas.

   There may further be significant inferential value to the research being repeated in relation to a different set of local authority areas in order to identify the extent to which the reported effect could be associated with those specific samples selected.

2. Similarly, supplementing the outlined research with qualitative and mixed-methods approaches to support understanding of the influence of local decisions and external actors upon rates of development (Cullingworth and Nadin, 2003) would permit a more nuanced analysis of the causal relationship between the policy and land change (Hersperger et al., 2018), whilst contributing towards the advancement of a theory of change model currently absent from the agenda (Hersperger et al., 2010). In this regard, the thesis could offer a foundation upon which to build a qualitative research basis challenging the assumptions underpinning the research.

3. Addressing issues related to the confidence of the temporal dynamics associated with the policy should further be considered critical. To achieve such, future analyses should be designed to incorporate planning application data, openly accessible via either user interface systems or increasingly application programming interfaces (ul Hussnain et al., 2020). However to undertake such, geo-located data would be required, which was shown to be insufficient to support this research.

4. The extent to which the outcomes evidenced by this thesis may be deemed to have been influenced by the input change data should further be tested. Relevant land change data should be obtained based upon remote sensed images, enabling analysis to potentially discern deterioration in the quality of green space [through vegetation indices] not available in the vector resources originally relied upon.

5. It is suggested the effects of national policies can only be analysed appropriately at a national scale (Verde et al., 2020), particularly where consideration is given to land change, which is likely to be evidenced differently at different spatial scales (Dallimer et al., 2011). However, this research was restricted to an aggregated sample primarily as a result of practical limitations. With national scale analysis a priority, subsequent research could employ sequential coding and clusters or super-computer resources in order to expand the methods to a national scale.

6. Through the application of similar approaches, in conjunction with methods such as *Qualitative Comparative Analysis*, it may be possible to develop an understanding of the role of policy in determining the type of

land undergoing change (Kasraian et al., 2019). Such would rely upon the detailed identification of land use and land cover types with relevant data (primarily in the form of binary variables) for the existence of key social and physical conditions.

7. In light of the diverse outcomes intended to be achieved through planning policy future studies should seek to adopt different indicative variables, such as the number of new residential buildings. Such data is available through governmental resources and could be accessed easily to support analysis of an intervention effect.

8.2 Conclusion

The influence of national level planning policy over rates and patterns of land use change represents a growing concern as developmental pressure upon natural land increases (Biello, 2012; Seto et al., 2012). Despite its significance few studies have been undertaken through which to explore this relationship based upon quantitative methods of analysis (Hersperger et al., 2018). The development of this field of study through *ex post facto* impact evaluation of implemented policies is considered imperative (Morrison and Pearce, 2000; Shahab et al., 2019).

This research addressed this issue using the example of the transition to the *Localism Act 2011* and *National Planning Policy Framework*, investigating the extent to which novel data and methods could identify the existence of a structural change attributable to policy [**RQ 1**], quantify the effect of the policy change [**RQ 2**] and the extent to which it resulted in different effects upon distinct 'urban' and 'rural' land [**RQ 3**]. Cumulatively the research findings indicate the change from the prior framework to the *NPPF* resulted in a significant increase in the rate at which development occurred upon green space. This increase appears to have been largely concentrated on land situated outside of extant urban limits. Accordingly, the revised policy framework can be empirically presented as a change in emphasis towards a system which is more permissive of urban expansion.

Under the Coalition and subsequently Conservative governments between 2010 and 2018, green space has been subject to a greater developmental threat than would likely have been evidenced under the preceding framework administered by New Labour. With provisions including the "*presumption in favour of sustainable development*" (National Planning Policy Framework [s.14]) and weakening of 'brownfield' first commitments hypothesised as critical changes.

These elements extend knowledge relating to the role of policy as a driver of land use change, addressing issues identified by Plieninger et al. (2016) and Morrison and Pearce (2000). Overall, it provides evidence of a causal relationship through the use of novel methods (in the form of *Change Point Detection* and *Interrupted Time Series* Analysis) and suggest relatively minimal policy reform can have a profound effect upon a development profile within time frames not previously considered plausible. *Wordsworth's* enervated epitaph for the loss of natural land appears to have been forgotten.

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APPENDIX A

A.1 Full Change Methodology

A.1.1 Stage 1: All Recorded Change

The first step in change identification utilised the fact that the unique ID of any new topographical object recorded in the data at time T would not exist in the equivalent data for time T_{-1}. Such would not imply that the new polygon necessarily constituted a genuine change, but provided the basis for subsequent stages.

Instances where a feature had been given a new ID, but ostensibly remained the same, in so far as it retained an identical '*make*' classifier and constituted 95% of the original area were removed. To achieve this, the area of spatial intersection was calculated between the polygons from times T and T_{-1}. Said area was subsequently divided both by the areas of the original shape (time T_{-1}) and new polygon(time T). Only where both derived values were equal to or greater than 0.95 was the object removed.

The resultant is referred to hereafter as 'provisional change' data.

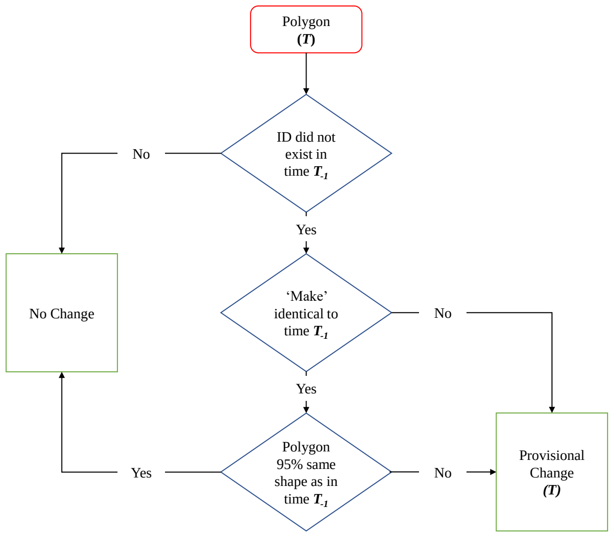

Figure A.1: Stage 1 minimum change identification process.

A.1.2 Stage 2: Identification of Prestige Buildings and New Residential Features

Based upon their prominence within the revision policy, both buildings associated with a *Prestige site* and all new residential developments were prioritised (Ordnance Survey, 2020). The identification of relevant built changes can most clearly be understood in two steps, which were elements of a single nested spatial join function.

Firstly, the 'provisional change' data was restricted to features which could be identified as a 'building' based upon the '*Descriptive Group*' classifier. Where said 'building' was shown to contain an *AddressBase Premium*® record, which identified it as one of 26 relevant classification codes (which only existed in the data after time T_{-1}) it was recorded as a change [**figure** A.2].

Figure A.2: An example of a Prestige Building or *Category A* new residential development (Ordnance Survey, 2020) identified using *AddressBase Premium*® spatial point data.

To ensure the identification of all buildings which could be deemed to be associated with or likely identified concurrently with prestige buildings or residential developments an additional stage was undertaken. Firstly, an indicative development site was identified as the original polygon (from time T_{-1}) upon which the change had occurred. Subsequently, all buildings with a new ID contained within said development site were assumed to represent genuine developmental change and included within the data [**figure** A.3].

Figure A.3: Derived indicative development site boundary with all new buildings. Those in grey represent buildings identified using *AddressBase Premium*® data. Whilst those in red represent buildings identified as part of the development site.

Finally all new features categorised as 'manmade' or 'multiple' (Ordnance Survey, 2020) which connected to an identified building were incorporated [refer to **figure** A.4]. A summary of the individual elements which were undertaken in this stage are presented in **figure** A.5

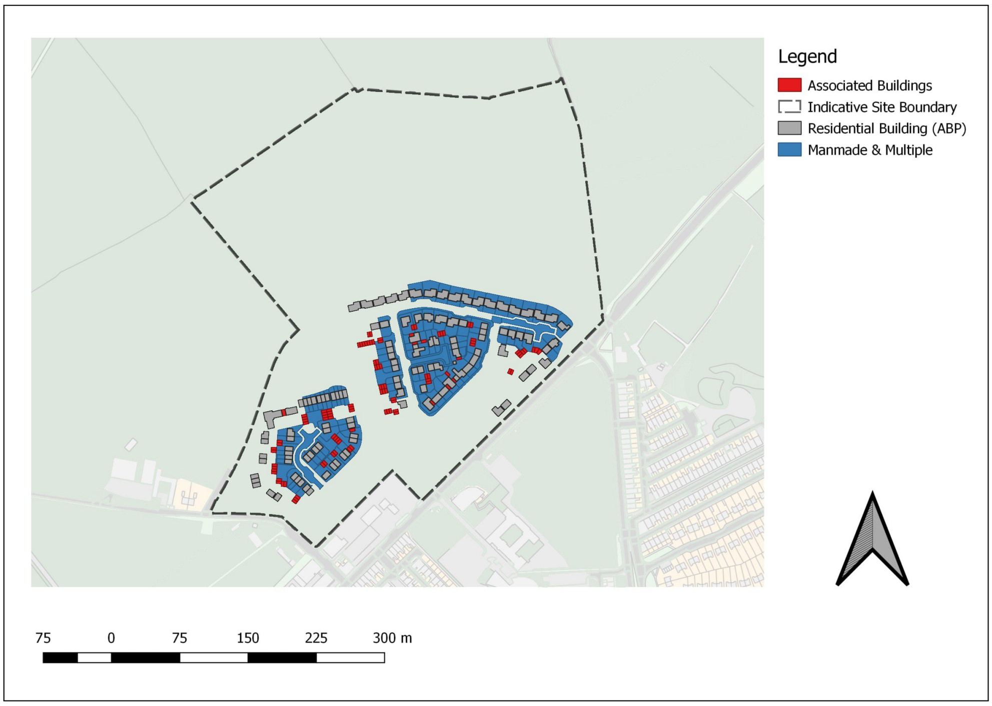

Figure A.4: Identified new built infrastructure associated with new buildings (represented in blue).

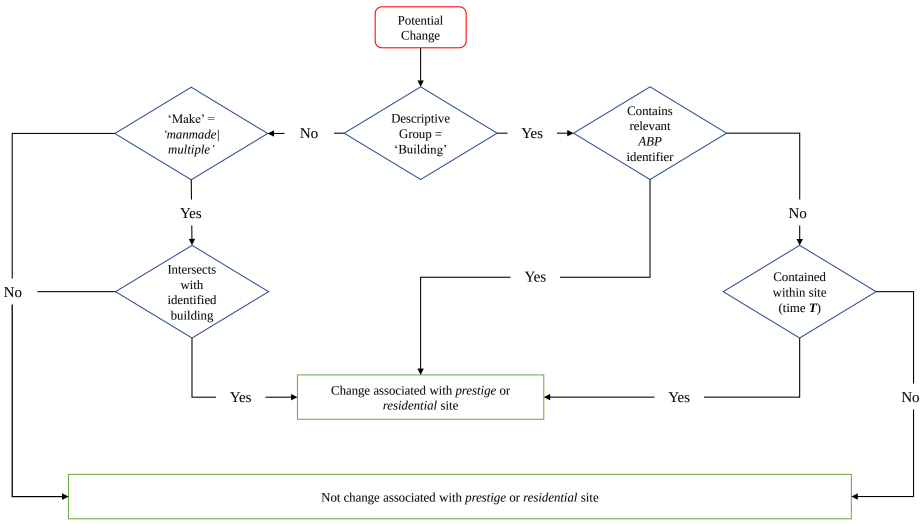

Figure A.5: Stage 2 minimum change identification process.

A.1.3 Stage 3: Retail and Industrial Development

In regards to both retail and industrial development included within the terms of *Category A* change, a broadly similar approach to **stage 2** was applied.

Initially therefore, appropriate developments were designated as any new building (as identified in **stage 1**) within which an *AddressBase Premium*® record indicated it was a commercial retail or industrial site not associated with agriculture (Ordnance Survey, 2020).

The site upon which said development took place was separately identified through the use of spatial functions and any unidentified building contained within such was incorporated into the change data. Thereafter, all other new 'manamde' features which intersected with the defined buildings were joined as constituents of change data [refer to **figure** A.6].

Figure A.6: Example of identified new industrial development with associated infrastructure.

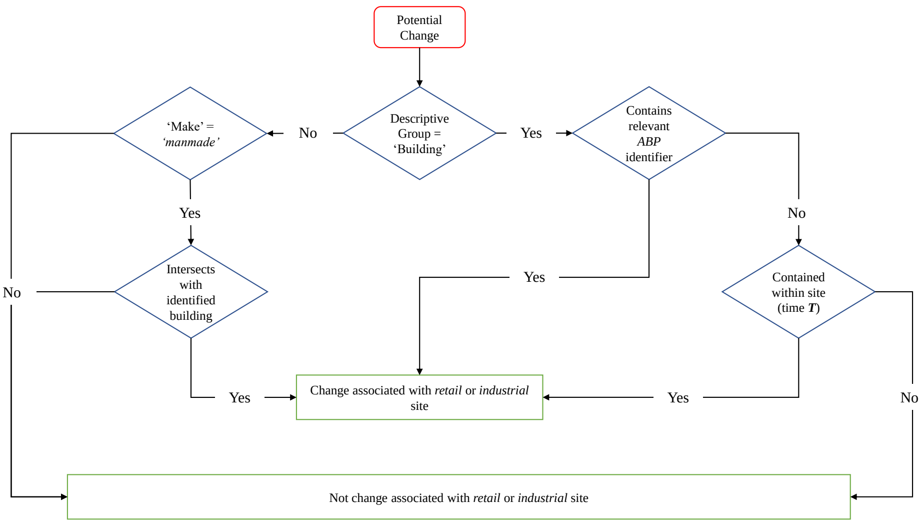

Figure A.7: Stage 3 minimum change identification process.

A.1.4 Stage 4: Agricultural Developments

Within the revision policy, both new and expanded built features associated with agricultural sites must be of 0.25 Ha or greater in order to be classified as *Category A* and thus identified within 6 months of occurrence. Due to the terms of the outlined condition it was possible to identify both new and extended features within a single stage.

Consequently, such sites were distinguished within the data using an adapted approach. Where previously the initial stage of identification was based upon relevant *AddressBase Premium*® data being contained within a new building, for agricultural sites it included association with any recorded 'manmade' surface [refer to **figure** A.8].

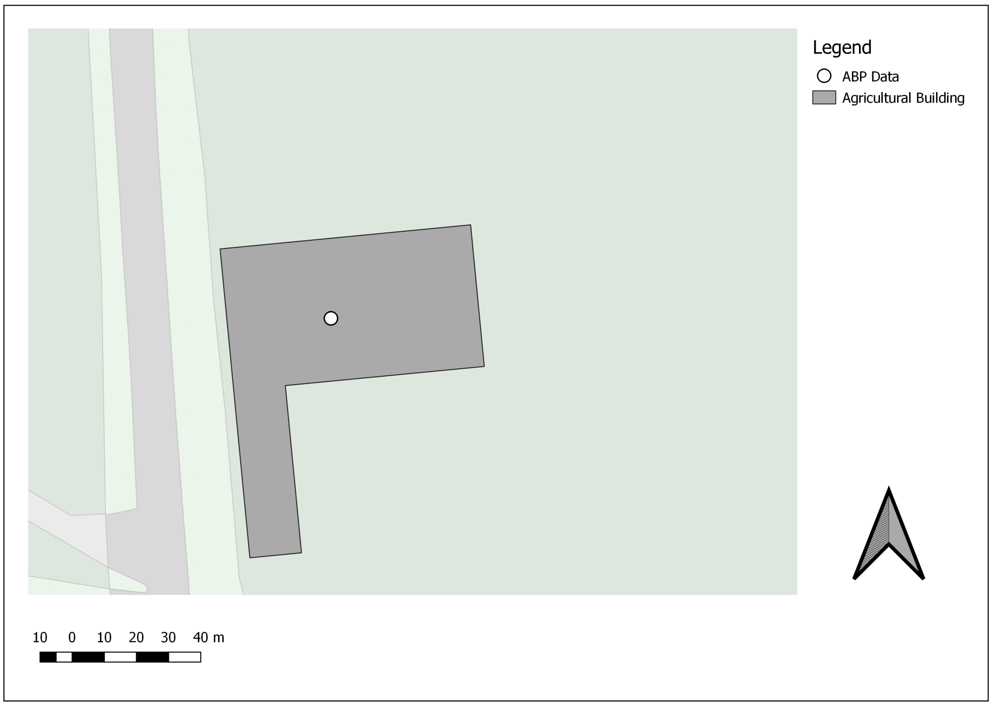

Figure A.8: Example of identified new agricultural building based upon *AddressBase Premium*® record.

Secondly, connected new 'manmade' features, which could be deemed to constitute the overall agricultural site were discerned [**figure A.9**] based upon a proximity criteria to the originally identified agricultural form. This technique replicated relevant governmental land use change methods (DCLG, 2015a).

Figure A.9: All 'manmade' features connected to the initially identified agricultural building. Blue features represent general 'manmade' surfaces, whilst red polygons denote additional buildings.

The subsequently identified agricultural site was amalgamated into a single polygonal form based upon a spatial clustering function. The relative area for this indicative site was calculated and if equal to or in excess of 2500m^2, its constituent elements were included within the relevant change data [refer to **figure** A.10].

Figure A.10: A complete new agricultural site consisting of 5 features.

In the outlined example the agricultural site comprised 5 individual elements, including two buildings and three general surfaces (representing associated hard standing). As the site was less than 0.25 Ha it was not identified as constituting a *Category A* change and consequently was not included within the 'minimum change' data.

ID	OS Descriptive Group Classifier	Area (m^2)
1000002562087720	Building	758.98
1000002562087716	General Surface	642.44
5000005194840898	General Surface	583.52
5000005194840822	General Surface	103.32
5000005194841092	Building	73.92
Total		**2,162.18**

A final flow chart is included in order to provide greater clarity in regards to the elements of the stage [**figure A.11**].

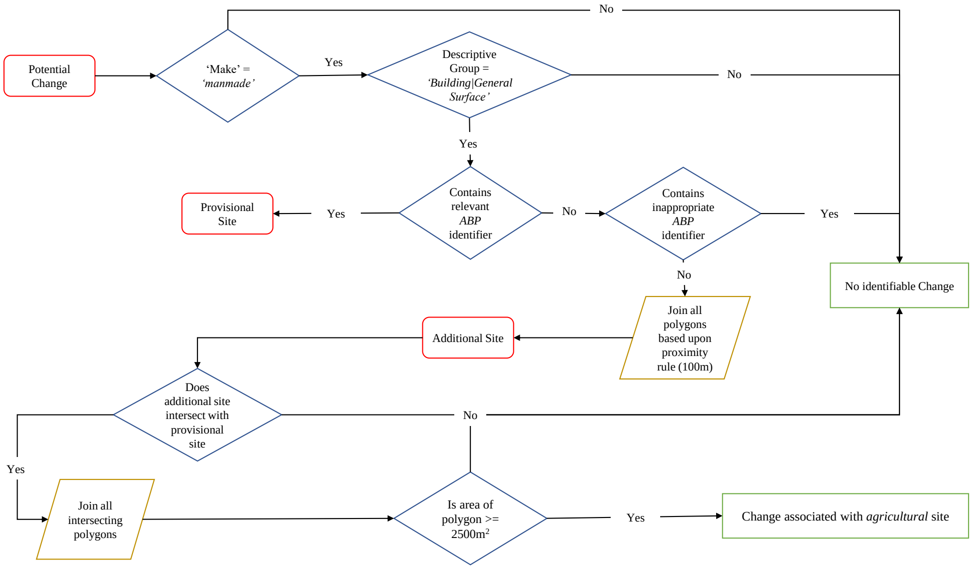

Figure A.11: Stage 4 minimum change identification process.

A.1.5 Stage 5: Developmental Preparation

Although excluded from the government's land use change methodology (DCLG, 2015a), *OS* categorise land which is in the process of undergoing development using the 'unclassified' designation (Ordnance Survey, 2017). Consequently, it is feasible to identify land at the earliest stages of development and include such as a form of change. This encompasses both the occurrence of development upon designated 'natural' and existing built forms [**Figures A.12** and **A.13**].

Figure A.12: Site in time T_{-1} consisting of both 'natural' and 'non-natural' features.

Figure A.13: Site at time T, in which it has undergone change to 'unclassified'.

As the ID of an 'unclassified' polygon remains the same as the largest feature it has replaced, such data was not identified as an element of the 'provisional change' data set produced in **stage 1**. Therefore, the identification of land subject to development between time intervals can be understood to reflect the spatial intersection of two polygons, which were classified as one form at time T_{-1}, but have become 'unclassified' in time T.

Whilst not explicitly outlined, it is assumed the primary reason for the omission of changes to 'unclassified' form was based upon the fact that the development may subsequently restore elements consistent with the previous 'make'. Thus not necessarily reflecting a genuine change of land use. However, with the research focus upon understanding the impact of development it was deemed imperative to include such.

Consequently, there is the potential to over-estimate the area of land lost permanently to development. However evidence suggests green space land directly associated with developments is often perceived as inaccessible (Wendel et al., 2012). Whilst additionally, it offers the only means by which to identify large scale developments, which may occur over many years, at a point more consistent with their approval. Furthermore, with an identical methodology applied to the entire data set the inclusion of such should not be deemed to compromise derived inferences.

A.1.6 Stage 6: Combined Change

Having created four distinct change data sets (**stages 2** to **5**), the individual elements were joined into a single multi-polygon file reflecting the minimum change which had occurred in time T. The initial estimation of the area to have undergone transition from green space to indicative developed form, therefore represented the spatial intersection between any area identified as 'natural' in time T_{-1} and the derived change dataset [**figure A.14**].

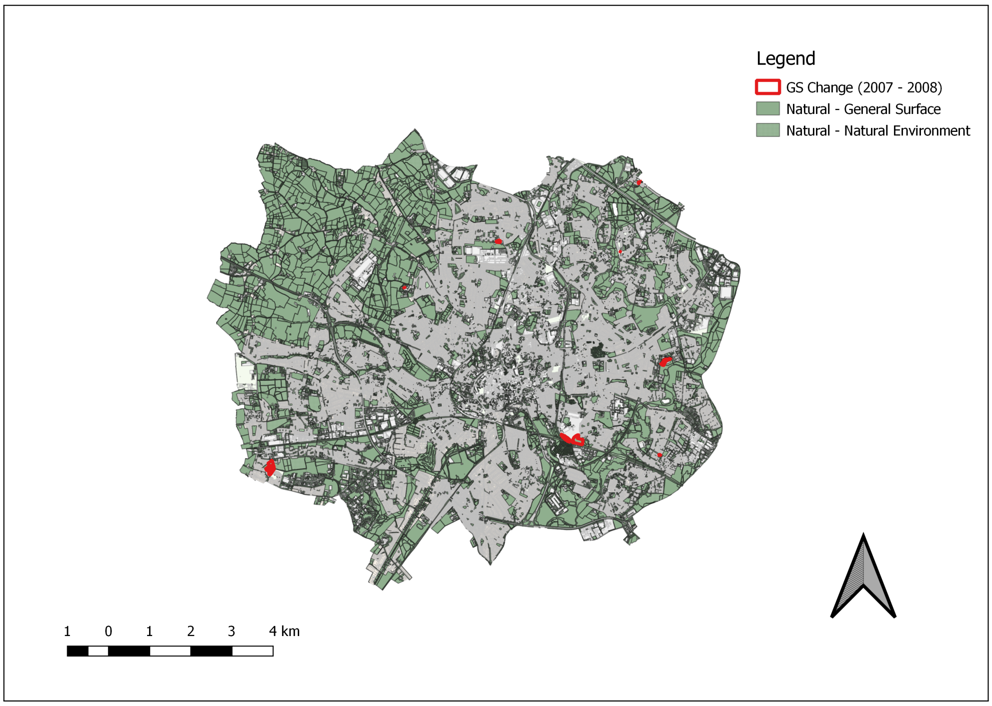

Figure A.14: An example of the total identified area of change from 'natural' to indicative developed form in a single LAA [Coventry] between 2007 and 2008.

A.1.7 Stage 7: Removal of Indicative 'Brownfield' Change

Where based solely upon the designation of land as 'natural', sites were included which would be categorised as 'brownfield' for the purpose of planning policy. Therefore, in any circumstance in which the 'natural' space (in time T_{-1}) upon which development occurred contained an *AddressBase Premium*® classification code denoting the existence of built infrastructure at any pint prior to time T_{-1} it was removed from the '*green space loss*' data.

APPENDIX B

B.1 Green Space Loss Data

Local Authority	Year	Quarter	Time Period	Recorded Area Green Space (2007 - Chng)	GS Loss (m^2)
Babergh	2007	1	1	549082546.2	0
Babergh	2007	2	2	549082546.2	14804.62
Babergh	2007	3	3	549067741.6	21112.96
Babergh	2007	4	4	549046628.6	29558.06
Babergh	2008	1	5	549017070.6	23764.97
Babergh	2008	2	6	548993305.6	0.01
Babergh	2008	3	7	548993305.6	46829.69
Babergh	2008	4	8	548946475.9	1588.86
Babergh	2009	1	9	548944887	15747.05
Babergh	2009	2	10	548929140	21095.07
Babergh	2009	3	11	548908044.9	7562.09
Babergh	2009	4	12	548900482.8	49324.51
Babergh	2010	1	13	548851158.3	5736.17
Babergh	2010	2	14	548845422.1	3997.01
Babergh	2010	3	15	548841425.1	15325.18
Babergh	2010	4	16	548826100	7516.83
Babergh	2011	1	17	548818583.1	31123.96
Babergh	2011	2	18	548787459.2	6546.76
Babergh	2011	3	19	548780912.4	0
Babergh	2011	4	20	548780912.4	80609.12
Babergh	2012	1	21	548700303.3	4426.42
Babergh	2012	2	22	548695876.9	6173.14
Babergh	2012	3	23	548689703.7	117136.47
Babergh	2012	4	24	548572567.2	1314.39
Babergh	2013	1	25	548571252.9	20229.07
Babergh	2013	2	26	548551023.8	0
Babergh	2013	3	27	548551023.8	19962.38
Babergh	2013	4	28	548531061.4	5814.61
Babergh	2014	1	29	548525246.8	4174.59
Babergh	2014	2	30	548521072.2	0
Babergh	2014	3	31	548521072.2	29765.91
Babergh	2014	4	32	548491306.3	47708.68
Babergh	2015	1	33	548443597.6	986.82
Babergh	2015	2	34	548442610.8	53667.88
Babergh	2015	3	35	548388942.9	10545.74
Babergh	2015	4	36	548378397.2	1847.33
Babergh	2016	1	37	548376549.9	2253.44
Babergh	2016	2	38	548374296.4	215.4
Babergh	2016	3	39	548374081	23460.82
Babergh	2016	4	40	548350620.2	26067.58
Babergh	2017	1	41	548324552.6	13410.22
Babergh	2017	2	42	548311142.4	0
Babergh	2017	3	43	548311142.4	30417.39
Babergh	2017	4	44	548280725	18393.17
Babergh	2018	1	45	548262331.8	63977.86
Babergh	2018	2	46	548198354	7627.49
Babergh	2018	3	47	548190726.5	12480.33
Babergh	2018	4	48	548178246.1	200181.24
Barrow-in-Furness	2007	1	1	60875896.36	578.19
Barrow-in-Furness	2007	2	2	60875318.17	0
Barrow-in-Furness	2007	3	3	60875318.17	0.01
Barrow-in-Furness	2007	4	4	60875318.16	0

Barrow-in-Furness	2008	1	5	60875318.16	0
Barrow-in-Furness	2008	2	6	60875318.16	0
Barrow-in-Furness	2008	3	7	60875318.16	0
Barrow-in-Furness	2008	4	8	60875318.16	0
Barrow-in-Furness	2009	1	9	60875318.16	0
Barrow-in-Furness	2009	2	10	60875318.16	59.03
Barrow-in-Furness	2009	3	11	60875259.13	0
Barrow-in-Furness	2009	4	12	60875259.13	1123.29
Barrow-in-Furness	2010	1	13	60874135.83	0
Barrow-in-Furness	2010	2	14	60874135.83	0
Barrow-in-Furness	2010	3	15	60874135.83	106.72
Barrow-in-Furness	2010	4	16	60874029.11	16662.44
Barrow-in-Furness	2011	1	17	60857366.67	0
Barrow-in-Furness	2011	2	18	60857366.67	0
Barrow-in-Furness	2011	3	19	60857366.67	0
Barrow-in-Furness	2011	4	20	60857366.67	568.26
Barrow-in-Furness	2012	1	21	60856798.41	0
Barrow-in-Furness	2012	2	22	60856798.41	0
Barrow-in-Furness	2012	3	23	60856798.41	0.08
Barrow-in-Furness	2012	4	24	60856798.33	0
Barrow-in-Furness	2013	1	25	60856798.33	0
Barrow-in-Furness	2013	2	26	60856798.33	5957.44
Barrow-in-Furness	2013	3	27	60850840.89	0
Barrow-in-Furness	2013	4	28	60850840.89	25257.59
Barrow-in-Furness	2014	1	29	60825583.31	114430.97
Barrow-in-Furness	2014	2	30	60711152.33	1144.08
Barrow-in-Furness	2014	3	31	60710008.26	842.82
Barrow-in-Furness	2014	4	32	60709165.43	1780.69
Barrow-in-Furness	2015	1	33	60707384.74	0
Barrow-in-Furness	2015	2	34	60707384.74	1773.94
Barrow-in-Furness	2015	3	35	60705610.8	11993.18
Barrow-in-Furness	2015	4	36	60693617.62	85714.71
Barrow-in-Furness	2016	1	37	60607902.91	0
Barrow-in-Furness	2016	2	38	60607902.91	0
Barrow-in-Furness	2016	3	39	60607902.91	0
Barrow-in-Furness	2016	4	40	60607902.91	0
Barrow-in-Furness	2017	1	41	60607902.91	709.42
Barrow-in-Furness	2017	2	42	60607193.49	677.29
Barrow-in-Furness	2017	3	43	60606516.2	45647.34
Barrow-in-Furness	2017	4	44	60560868.86	2303.96
Barrow-in-Furness	2018	1	45	60558564.9	0
Barrow-in-Furness	2018	2	46	60558564.9	305.05
Barrow-in-Furness	2018	3	47	60558259.85	0
Barrow-in-Furness	2018	4	48	60558259.85	10265.9
Birmingham	2007	1	1	90232756.08	941.35
Birmingham	2007	2	2	90231814.73	210719.83
Birmingham	2007	3	3	90021094.9	14805.08
Birmingham	2007	4	4	90006289.81	10981.04
Birmingham	2008	1	5	89995308.77	837.83
Birmingham	2008	2	6	89994470.95	1837.71
Birmingham	2008	3	7	89992633.23	9275.98
Birmingham	2008	4	8	89983357.25	7090.46
Birmingham	2009	1	9	89976266.79	6906.41
Birmingham	2009	2	10	89969360.39	0
Birmingham	2009	3	11	89969360.39	9997.37
Birmingham	2009	4	12	89959363.02	41019.42
Birmingham	2010	1	13	89918343.59	18424.5
Birmingham	2010	2	14	89899919.1	379.08
Birmingham	2010	3	15	89899540.02	13415.13
Birmingham	2010	4	16	89886124.89	747.86
Birmingham	2011	1	17	89885377.02	8170.38
Birmingham	2011	2	18	89877206.64	15846.82
Birmingham	2011	3	19	89861359.82	5921.37
Birmingham	2011	4	20	89855438.45	18068.76
Birmingham	2012	1	21	89837369.69	38879.38
Birmingham	2012	2	22	89798490.32	2264.99
Birmingham	2012	3	23	89796225.32	1600.31
Birmingham	2012	4	24	89794625.02	3486.07
Birmingham	2013	1	25	89791138.94	5528.65
Birmingham	2013	2	26	89785610.29	26853.18
Birmingham	2013	3	27	89758757.11	12734.9
Birmingham	2013	4	28	89746022.21	116778.66
Birmingham	2014	1	29	89629243.56	17486.69
Birmingham	2014	2	30	89611756.87	1518.34
Birmingham	2014	3	31	89610238.53	41771.04
Birmingham	2014	4	32	89568467.49	43418.87

Birmingham	2015	1	33	89525048.62	15930.1
Birmingham	2015	2	34	89509118.52	63994.74
Birmingham	2015	3	35	89445123.77	45080.54
Birmingham	2015	4	36	89400043.23	9503.65
Birmingham	2016	1	37	89390539.58	4539.38
Birmingham	2016	2	38	89386000.2	7761.79
Birmingham	2016	3	39	89378238.41	40275.79
Birmingham	2016	4	40	89337962.63	62288.99
Birmingham	2017	1	41	89275673.64	41918.13
Birmingham	2017	2	42	89233755.51	6765.27
Birmingham	2017	3	43	89226990.24	56090.84
Birmingham	2017	4	44	89170899.4	2211.2
Birmingham	2018	1	45	89168688.2	12928.14
Birmingham	2018	2	46	89155760.06	80743.78
Birmingham	2018	3	47	89075016.28	5846.46
Birmingham	2018	4	48	89069169.82	27405.26
Blaby	2007	1	1	103596834.4	7714.02
Blaby	2007	2	2	103589120.4	30.73
Blaby	2007	3	3	103589089.7	0
Blaby	2007	4	4	103589089.7	0
Blaby	2008	1	5	103589089.7	155.43
Blaby	2008	2	6	103588934.2	3999.17
Blaby	2008	3	7	103584935.1	1346.17
Blaby	2008	4	8	103583588.9	1468.86
Blaby	2009	1	9	103582120	29847.2
Blaby	2009	2	10	103552272.8	1318.46
Blaby	2009	3	11	103550954.4	0
Blaby	2009	4	12	103550954.4	0
Blaby	2010	1	13	103550954.4	5745.28
Blaby	2010	2	14	103545209.1	1923.13
Blaby	2010	3	15	103543286	65791.2
Blaby	2010	4	16	103477494.8	687.79
Blaby	2011	1	17	103476807	32621.93
Blaby	2011	2	18	103444185	64675.57
Blaby	2011	3	19	103379509.5	299.25
Blaby	2011	4	20	103379210.2	0.01
Blaby	2012	1	21	103379210.2	0
Blaby	2012	2	22	103379210.2	7030.1
Blaby	2012	3	23	103372180.1	89210.17
Blaby	2012	4	24	103282969.9	3348.26
Blaby	2013	1	25	103279621.7	2861.94
Blaby	2013	2	26	103276759.7	7297.59
Blaby	2013	3	27	103269462.1	3779.27
Blaby	2013	4	28	103265682.9	102659.27
Blaby	2014	1	29	103163023.6	365306.95
Blaby	2014	2	30	102797716.7	26499.02
Blaby	2014	3	31	102771217.6	9750.44
Blaby	2014	4	32	102761467.2	123660.9
Blaby	2015	1	33	102637806.3	269601.32
Blaby	2015	2	34	102368205	6040.52
Blaby	2015	3	35	102362164.5	40038.69
Blaby	2015	4	36	102322125.8	147058.58
Blaby	2016	1	37	102175067.2	71584.96
Blaby	2016	2	38	102103482.2	62728.84
Blaby	2016	3	39	102040753.4	1463.83
Blaby	2016	4	40	102039289.6	107558.75
Blaby	2017	1	41	101931730.8	351403.43
Blaby	2017	2	42	101580327.4	140597.23
Blaby	2017	3	43	101439730.2	30706.68
Blaby	2017	4	44	101409023.5	75437.69
Blaby	2018	1	45	101333585.8	4141.23
Blaby	2018	2	46	101329444.5	5104.51
Blaby	2018	3	47	101324340	82087
Blaby	2018	4	48	101242253	125225.36
Boston	2007	1	1	317654473.2	15966.92
Boston	2007	2	2	317638506.3	25020.47
Boston	2007	3	3	317613485.8	20029.91
Boston	2007	4	4	317593455.9	11860.03
Boston	2008	1	5	317581595.9	20114.33
Boston	2008	2	6	317561481.5	1.87
Boston	2008	3	7	317561479.7	2571.48
Boston	2008	4	8	317558908.2	622.95
Boston	2009	1	9	317558285.3	3512.69
Boston	2009	2	10	317554772.6	0
Boston	2009	3	11	317554772.6	608.15
Boston	2009	4	12	317554164.4	2660.53

Boston	2010	1	13	317551503.9	7291.79
Boston	2010	2	14	317544212.1	0
Boston	2010	3	15	317544212.1	0
Boston	2010	4	16	317544212.1	0
Boston	2011	1	17	317544212.1	21678.38
Boston	2011	2	18	317522533.7	0
Boston	2011	3	19	317522533.7	12984.96
Boston	2011	4	20	317509548.8	0
Boston	2012	1	21	317509548.8	2201.74
Boston	2012	2	22	317507347	0
Boston	2012	3	23	317507347	3075.78
Boston	2012	4	24	317504271.2	29768.31
Boston	2013	1	25	317474502.9	530.38
Boston	2013	2	26	317473972.6	0
Boston	2013	3	27	317473972.6	2801.83
Boston	2013	4	28	317471170.7	26648.28
Boston	2014	1	29	317444522.4	6835.39
Boston	2014	2	30	317437687	740.95
Boston	2014	3	31	317436946.1	4055.82
Boston	2014	4	32	317432890.3	20428.07
Boston	2015	1	33	317412462.2	664.29
Boston	2015	2	34	317411797.9	13194.09
Boston	2015	3	35	317398603.8	2203.74
Boston	2015	4	36	317396400.1	58845.97
Boston	2016	1	37	317337554.1	42578.08
Boston	2016	2	38	317294976	10373.57
Boston	2016	3	39	317284602.5	32041.56
Boston	2016	4	40	317252560.9	14468.86
Boston	2017	1	41	317238092.1	4942.08
Boston	2017	2	42	317233150	130615.25
Boston	2017	3	43	317102534.7	54070.42
Boston	2017	4	44	317048464.3	70416.25
Boston	2018	1	45	316978048.1	8252.77
Boston	2018	2	46	316969795.3	7689.64
Boston	2018	3	47	316962105.7	23675.54
Boston	2018	4	48	316938430.1	87613
Brentwood	2007	1	1	129795916.5	0
Brentwood	2007	2	2	129795916.5	842.8761868
Brentwood	2007	3	3	129795073.6	0
Brentwood	2007	4	4	129795073.6	2141.339395
Brentwood	2008	1	5	129792932.3	78.51162567
Brentwood	2008	2	6	129792853.8	0
Brentwood	2008	3	7	129792853.8	2413.139908
Brentwood	2008	4	8	129790440.6	0.037154729
Brentwood	2009	1	9	129790440.6	0
Brentwood	2009	2	10	129790440.6	0
Brentwood	2009	3	11	129790440.6	2868.335866
Brentwood	2009	4	12	129787572.3	0
Brentwood	2010	1	13	129787572.3	0.185136696
Brentwood	2010	2	14	129787572.1	0.000632187
Brentwood	2010	3	15	129787572.1	0
Brentwood	2010	4	16	129787572.1	0
Brentwood	2011	1	17	129787572.1	0
Brentwood	2011	2	18	129787572.1	0
Brentwood	2011	3	19	129787572.1	1459.6071
Brentwood	2011	4	20	129786112.5	686.5342408
Brentwood	2012	1	21	129785425.9	301.8124126
Brentwood	2012	2	22	129785124.1	0
Brentwood	2012	3	23	129785124.1	2567.741224
Brentwood	2012	4	24	129782556.4	0
Brentwood	2013	1	25	129782556.4	8421.081733
Brentwood	2013	2	26	129774135.3	0
Brentwood	2013	3	27	129774135.3	0
Brentwood	2013	4	28	129774135.3	239.7763101
Brentwood	2014	1	29	129773895.5	6643.862664
Brentwood	2014	2	30	129767251.7	3094.575978
Brentwood	2014	3	31	129764157.1	0
Brentwood	2014	4	32	129764157.1	5211.0845
Brentwood	2015	1	33	129758946	4443.999076
Brentwood	2015	2	34	129754502	1310.547726
Brentwood	2015	3	35	129753191.5	25786.40814
Brentwood	2015	4	36	129727405	0
Brentwood	2016	1	37	129727405	1153.505028
Brentwood	2016	2	38	129726251.5	880.6111525
Brentwood	2016	3	39	129725370.9	8.04490376
Brentwood	2016	4	40	129725362.9	6759.858084

Brentwood	2017	1	41	129718603	1753.9485
Brentwood	2017	2	42	129716849.1	120.9222208
Brentwood	2017	3	43	129716728.2	21890.23879
Brentwood	2017	4	44	129694837.9	3860.597334
Brentwood	2018	1	45	129690977.3	6405.745891
Brentwood	2018	2	46	129684571.6	0
Brentwood	2018	3	47	129684571.6	15087.20724
Brentwood	2018	4	48	129669484.4	1980.952122
Bristol, City of	2007	1	1	39619535.85	2089.21311
Bristol, City of	2007	2	2	39617446.64	56909.50143
Bristol, City of	2007	3	3	39560537.14	49750.00054
Bristol, City of	2007	4	4	39510787.13	2724.472663
Bristol, City of	2008	1	5	39508062.66	4433.773602
Bristol, City of	2008	2	6	39503628.89	21465.33501
Bristol, City of	2008	3	7	39482163.55	223.3338264
Bristol, City of	2008	4	8	39481940.22	131564.8489
Bristol, City of	2009	1	9	39350375.37	65622.49828
Bristol, City of	2009	2	10	39284752.87	528.9332689
Bristol, City of	2009	3	11	39284223.94	18938.67195
Bristol, City of	2009	4	12	39265285.27	7524.164497
Bristol, City of	2010	1	13	39257761.1	30471.51792
Bristol, City of	2010	2	14	39227289.58	64053.31117
Bristol, City of	2010	3	15	39163236.27	5290.416392
Bristol, City of	2010	4	16	39157945.86	10101.91182
Bristol, City of	2011	1	17	39147843.95	1555.211691
Bristol, City of	2011	2	18	39146288.73	734.81637
Bristol, City of	2011	3	19	39145553.92	1741.420642
Bristol, City of	2011	4	20	39143812.5	0.005125501
Bristol, City of	2012	1	21	39143812.49	81.59094386
Bristol, City of	2012	2	22	39143730.9	9909.498919
Bristol, City of	2012	3	23	39133821.4	7774.479299
Bristol, City of	2012	4	24	39126046.92	24757.88488
Bristol, City of	2013	1	25	39101289.04	3993.512267
Bristol, City of	2013	2	26	39097295.53	81.43940791
Bristol, City of	2013	3	27	39097214.09	1151.719346
Bristol, City of	2013	4	28	39096062.37	16684.47609
Bristol, City of	2014	1	29	39079377.89	8984.256361
Bristol, City of	2014	2	30	39070393.63	292.1532467
Bristol, City of	2014	3	31	39070101.48	563.493227
Bristol, City of	2014	4	32	39069537.99	2792.203374
Bristol, City of	2015	1	33	39066745.78	1824.069577
Bristol, City of	2015	2	34	39064921.71	17468.65703
Bristol, City of	2015	3	35	39047453.06	194.701214
Bristol, City of	2015	4	36	39047258.36	42889.63514
Bristol, City of	2016	1	37	39004368.72	43.26300434
Bristol, City of	2016	2	38	39004325.46	15846.61779
Bristol, City of	2016	3	39	38988478.84	913.1429522
Bristol, City of	2016	4	40	38987565.7	49374.35505
Bristol, City of	2017	1	41	38938191.34	2444.096716
Bristol, City of	2017	2	42	38935747.25	20765.10201
Bristol, City of	2017	3	43	38914982.14	30755.64012
Bristol, City of	2017	4	44	38884226.5	909.4353262
Bristol, City of	2018	1	45	38883317.07	4527.761281
Bristol, City of	2018	2	46	38878789.31	36569.02695
Bristol, City of	2018	3	47	38842220.28	2020.419287
Bristol, City of	2018	4	48	38840199.86	17908.53332
Chiltern	2007	1	1	162336868	5450.2727
Chiltern	2007	2	2	162331417.7	0
Chiltern	2007	3	3	162331417.7	60.21669482
Chiltern	2007	4	4	162331357.5	0
Chiltern	2008	1	5	162331357.5	644.1488226
Chiltern	2008	2	6	162330713.4	0
Chiltern	2008	3	7	162330713.4	0
Chiltern	2008	4	8	162330713.4	0
Chiltern	2009	1	9	162330713.4	0
Chiltern	2009	2	10	162330713.4	366.33395
Chiltern	2009	3	11	162330347	736.6276
Chiltern	2009	4	12	162329610.4	19538.05906
Chiltern	2010	1	13	162310072.3	0
Chiltern	2010	2	14	162310072.3	4930.64035
Chiltern	2010	3	15	162305141.7	0.004961634
Chiltern	2010	4	16	162305141.7	534.29745
Chiltern	2011	1	17	162304607.4	0
Chiltern	2011	2	18	162304607.4	27678.41825
Chiltern	2011	3	19	162276929	0
Chiltern	2011	4	20	162276929	0.001710165

Chiltern	2012	1	21	162276929	0.889335045
Chiltern	2012	2	22	162276928.1	0.000289544
Chiltern	2012	3	23	162276928.1	0.000143213
Chiltern	2012	4	24	162276928.1	0.037337803
Chiltern	2013	1	25	162276928.1	0.001201082
Chiltern	2013	2	26	162276928.1	3.736223099
Chiltern	2013	3	27	162276924.3	0
Chiltern	2013	4	28	162276924.3	1580.475643
Chiltern	2014	1	29	162275343.8	0
Chiltern	2014	2	30	162275343.8	0
Chiltern	2014	3	31	162275343.8	37912.54052
Chiltern	2014	4	32	162237431.3	1337.003927
Chiltern	2015	1	33	162236094.3	57235.02432
Chiltern	2015	2	34	162178859.3	4.185027802
Chiltern	2015	3	35	162178855.1	0
Chiltern	2015	4	36	162178855.1	735.6027483
Chiltern	2016	1	37	162178119.5	8744.440632
Chiltern	2016	2	38	162169375	17127.43855
Chiltern	2016	3	39	162152247.6	12.17747789
Chiltern	2016	4	40	162152235.4	0.0029043
Chiltern	2017	1	41	162152235.4	1718.521848
Chiltern	2017	2	42	162150516.9	37172.03593
Chiltern	2017	3	43	162113344.9	784.1414221
Chiltern	2017	4	44	162112560.7	1807.440854
Chiltern	2018	1	45	162110753.3	2562.101404
Chiltern	2018	2	46	162108191.2	8048.999043
Chiltern	2018	3	47	162100142.2	1063.388206
Chiltern	2018	4	48	162099078.8	101.9111689
Cornwall	2007	1	1	2772543593	14897.69663
Cornwall	2007	2	2	2772528695	47355.73109
Cornwall	2007	3	3	2772481340	59471.47774
Cornwall	2007	4	4	2772421868	144909.8486
Cornwall	2008	1	5	2772276958	55142.79672
Cornwall	2008	2	6	2772221815	55375.31886
Cornwall	2008	3	7	2772166440	119540.7523
Cornwall	2008	4	8	2772046899	37998.2168
Cornwall	2009	1	9	2772008901	62823.93244
Cornwall	2009	2	10	2771946077	37454.571
Cornwall	2009	3	11	2771908623	91897.97732
Cornwall	2009	4	12	2771816725	29774.69585
Cornwall	2010	1	13	2771786950	70011.5204
Cornwall	2010	2	14	2771716938	147741.8291
Cornwall	2010	3	15	2771569197	89463.45341
Cornwall	2010	4	16	2771479733	100116.7255
Cornwall	2011	1	17	2771379616	58393.67438
Cornwall	2011	2	18	2771321223	71675.33408
Cornwall	2011	3	19	2771249547	73317.88943
Cornwall	2011	4	20	2771176230	69912.60462
Cornwall	2012	1	21	2771106317	56424.54858
Cornwall	2012	2	22	2771049892	44128.20235
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Cornwall	2013	1	25	2770882316	44505.47687
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Cornwall	2013	3	27	2770646882	94981.43451
Cornwall	2013	4	28	2770551900	99013.8548
Cornwall	2014	1	29	2770452887	138435.4281
Cornwall	2014	2	30	2770314451	209389.2927
Cornwall	2014	3	31	2770105062	93754.45913
Cornwall	2014	4	32	2770011307	227092.5046
Cornwall	2015	1	33	2769784215	101277.6402
Cornwall	2015	2	34	2769682937	95177.21654
Cornwall	2015	3	35	2769587760	333671.6763
Cornwall	2015	4	36	2769254088	178564.2037
Cornwall	2016	1	37	2769075524	72139.45692
Cornwall	2016	2	38	2769003385	44379.23822
Cornwall	2016	3	39	2768959005	178252.4241
Cornwall	2016	4	40	2768780753	140650.2809
Cornwall	2017	1	41	2768640103	48015.03027
Cornwall	2017	2	42	2768592088	72743.71131
Cornwall	2017	3	43	2768519344	536506.3135
Cornwall	2017	4	44	2767982838	50064.30884
Cornwall	2018	1	45	2767932773	24367.21571
Cornwall	2018	2	46	2767908406	22732.79723
Cornwall	2018	3	47	2767885673	107779.3544
Cornwall	2018	4	48	2767777894	20504.88864

County Durham	2007	1	1	2077147559	44668.27
County Durham	2007	2	2	2077102891	69528.65
County Durham	2007	3	3	2077033362	109939.01
County Durham	2007	4	4	2076923423	49632.55
County Durham	2008	1	5	2076873791	172343.26
County Durham	2008	2	6	2076701447	106347.15
County Durham	2008	3	7	2076595100	59989.4
County Durham	2008	4	8	2076535111	18788.18
County Durham	2009	1	9	2076516323	72284.48
County Durham	2009	2	10	2076444038	13853.58
County Durham	2009	3	11	2076430184	151993.92
County Durham	2009	4	12	2076278191	161045.12
County Durham	2010	1	13	2076117145	12648.64
County Durham	2010	2	14	2076104497	18183.61
County Durham	2010	3	15	2076086313	1857.25
County Durham	2010	4	16	2076084456	32992.98
County Durham	2011	1	17	2076051463	38715.62
County Durham	2011	2	18	2076012747	5579.98
County Durham	2011	3	19	2076007167	42004.28
County Durham	2011	4	20	2075965163	112220.43
County Durham	2012	1	21	2075852943	41003.25
County Durham	2012	2	22	2075811939	62289.1
County Durham	2012	3	23	2075749650	71406.98
County Durham	2012	4	24	2075678243	66691.11
County Durham	2013	1	25	2075611552	57183.01
County Durham	2013	2	26	2075554369	92824.73
County Durham	2013	3	27	2075461544	153955.59
County Durham	2013	4	28	2075307589	111399.61
County Durham	2014	1	29	2075196189	63809.1
County Durham	2014	2	30	2075132380	125631.97
County Durham	2014	3	31	2075006748	445960.15
County Durham	2014	4	32	2074560788	161054.32
County Durham	2015	1	33	2074399734	57950.25
County Durham	2015	2	34	2074341783	12826.81
County Durham	2015	3	35	2074328957	233074.17
County Durham	2015	4	36	2074095882	136744.49
County Durham	2016	1	37	2073959138	73000.97
County Durham	2016	2	38	2073886137	48540.34
County Durham	2016	3	39	2073837597	236796.42
County Durham	2016	4	40	2073600800	284184.19
County Durham	2017	1	41	2073316616	92596.51
County Durham	2017	2	42	2073224020	49701.43
County Durham	2017	3	43	2073174318	47489.51
County Durham	2017	4	44	2073126829	101242.3
County Durham	2018	1	45	2073025586	119151.68
County Durham	2018	2	46	2072906435	117964.17
County Durham	2018	3	47	2072788470	79818.95
County Durham	2018	4	48	2072708652	844206.19
Coventry	2007	1	1	43159162.54	38340.18
Coventry	2007	2	2	43120822.36	0
Coventry	2007	3	3	43120822.36	10788.75
Coventry	2007	4	4	43110033.61	52098.35
Coventry	2008	1	5	43057935.26	4044.89
Coventry	2008	2	6	43053890.38	15214.89
Coventry	2008	3	7	43038675.49	167.37
Coventry	2008	4	8	43038508.12	249.85
Coventry	2009	1	9	43038258.27	237.75
Coventry	2009	2	10	43038020.52	43.08
Coventry	2009	3	11	43037977.43	77766.21
Coventry	2009	4	12	42960211.23	16590.64
Coventry	2010	1	13	42943620.59	0
Coventry	2010	2	14	42943620.59	24323.56
Coventry	2010	3	15	42919297.03	44538.49
Coventry	2010	4	16	42874758.54	4012.54
Coventry	2011	1	17	42870746	0
Coventry	2011	2	18	42870746	16.58
Coventry	2011	3	19	42870729.41	13786.82
Coventry	2011	4	20	42856942.59	203.52
Coventry	2012	1	21	42856739.07	11264.83
Coventry	2012	2	22	42845474.23	6271.93
Coventry	2012	3	23	42839202.3	703.54
Coventry	2012	4	24	42838498.77	7565.4
Coventry	2013	1	25	42830933.37	28.32
Coventry	2013	2	26	42830905.05	41000.17
Coventry	2013	3	27	42789904.88	6376.48
Coventry	2013	4	28	42783528.4	1818.11

Coventry	2014	1	29	42781710.29	119.14
Coventry	2014	2	30	42781591.15	52792.29
Coventry	2014	3	31	42728798.86	3245.98
Coventry	2014	4	32	42725552.88	0
Coventry	2015	1	33	42725552.88	0.251324146
Coventry	2015	2	34	42725552.63	18514.39058
Coventry	2015	3	35	42725552.38	0.001138967
Coventry	2015	4	36	42707037.99	47690.95047
Coventry	2016	1	37	42707037.99	30466.69998
Coventry	2016	2	38	42659347.03	273055.0792
Coventry	2016	3	39	42628880.33	184.928777
Coventry	2016	4	40	42355825.26	8113.151973
Coventry	2017	1	41	42355640.33	84387.79178
Coventry	2017	2	42	42347527.17	12750.43647
Coventry	2017	3	43	42263139.38	30788.61687
Coventry	2017	4	44	42250388.95	0
Coventry	2018	1	45	42219600.33	841.9106605
Coventry	2018	2	46	42218758.42	64492.39239
Coventry	2018	3	47	42154266.03	33608.36484
Coventry	2018	4	48	42120657.66	94143.04222
Doncaster	2007	1	1	482133077.1	111073.6479
Doncaster	2007	2	2	482022003.5	506.568545
Doncaster	2007	3	3	482021496.9	4502.384773
Doncaster	2007	4	4	482016994.5	134022.1701
Doncaster	2008	1	5	481882972.3	3504.496969
Doncaster	2008	2	6	481879467.8	76.33051838
Doncaster	2008	3	7	481879391.5	10690.22582
Doncaster	2008	4	8	481868701.3	30554.15851
Doncaster	2009	1	9	481838147.1	39964.09827
Doncaster	2009	2	10	481798183	10414.43358
Doncaster	2009	3	11	481787768.6	12200.96142
Doncaster	2009	4	12	481775567.6	4211.7286
Doncaster	2010	1	13	481771355.9	18638.59711
Doncaster	2010	2	14	481752717.3	2052.314547
Doncaster	2010	3	15	481750665	44786.95177
Doncaster	2010	4	16	481705878	2899.063033
Doncaster	2011	1	17	481702979	78291.22525
Doncaster	2011	2	18	481624687.7	2096.133497
Doncaster	2011	3	19	481622591.6	937.4144591
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Doncaster	2012	1	21	481621653.6	38.32020013
Doncaster	2012	2	22	481621615.3	692.1694352
Doncaster	2012	3	23	481620923.1	8811.542596
Doncaster	2012	4	24	481612111.6	6073.799508
Doncaster	2013	1	25	481606037.8	50441.58868
Doncaster	2013	2	26	481555596.2	19973.12617
Doncaster	2013	3	27	481535623.1	8819.780039
Doncaster	2013	4	28	481526803.3	217846.6679
Doncaster	2014	1	29	481308956.6	168300.7073
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Doncaster	2014	4	32	480768573.3	23307.13288
Doncaster	2015	1	33	480745266.2	71855.39255
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Doncaster	2015	3	35	479477393.8	217152.7805
Doncaster	2015	4	36	479260241	150905.6742
Doncaster	2016	1	37	479109335.3	112926.4684
Doncaster	2016	2	38	478996408.9	106567.6867
Doncaster	2016	3	39	478889841.2	146687.4027
Doncaster	2016	4	40	478743153.8	299820.5969
Doncaster	2017	1	41	478443333.2	430961.62
Doncaster	2017	2	42	478012371.5	31171.08086
Doncaster	2017	3	43	477981200.5	497894.7411
Doncaster	2017	4	44	477483305.7	115076.4484
Doncaster	2018	1	45	477368229.3	96056.47527
Doncaster	2018	2	46	477272172.8	38385.66504
Doncaster	2018	3	47	477233787.1	580691.208
Doncaster	2018	4	48	476653095.9	6360.136999
East Staffordshire	2007	1	1	475142109.3	7834.995259
East Staffordshire	2007	2	2	475134274.3	42524.86951
East Staffordshire	2007	3	3	475091749.4	346.7815392
East Staffordshire	2007	4	4	475091402.7	84.65168623
East Staffordshire	2008	1	5	475091318	3026.504879
East Staffordshire	2008	2	6	475088291.5	14972.28778
East Staffordshire	2008	3	7	475073319.2	39924.80034
East Staffordshire	2008	4	8	475033394.4	0

East Staffordshire	2009	1	9	475033394.4	21281.34528
East Staffordshire	2009	2	10	475012113.1	0
East Staffordshire	2009	3	11	475012113.1	0
East Staffordshire	2009	4	12	475012113.1	798.9012
East Staffordshire	2010	1	13	475011314.2	6321.625411
East Staffordshire	2010	2	14	475004992.5	0
East Staffordshire	2010	3	15	475004992.5	19403.89375
East Staffordshire	2010	4	16	474985588.6	0
East Staffordshire	2011	1	17	474985588.6	11113.25578
East Staffordshire	2011	2	18	474974475.4	0
East Staffordshire	2011	3	19	474974475.4	2455.010192
East Staffordshire	2011	4	20	474972020.4	3088.314814
East Staffordshire	2012	1	21	474968932.1	2726.718802
East Staffordshire	2012	2	22	474966205.3	8339.890555
East Staffordshire	2012	3	23	474957865.5	8.28E-05
East Staffordshire	2012	4	24	474957865.5	45.46701661
East Staffordshire	2013	1	25	474957820	1277.783822
East Staffordshire	2013	2	26	474956542.2	156.1733544
East Staffordshire	2013	3	27	474956386	51821.79454
East Staffordshire	2013	4	28	474904564.2	6677.478693
East Staffordshire	2014	1	29	474897886.8	29578.81081
East Staffordshire	2014	2	30	474868307.9	0
East Staffordshire	2014	3	31	474868307.9	84311.85798
East Staffordshire	2014	4	32	474783996.1	2473.663901
East Staffordshire	2015	1	33	474781522.4	40969.99795
East Staffordshire	2015	2	34	474740552.4	10077.91324
East Staffordshire	2015	3	35	474730474.5	7809.10423
East Staffordshire	2015	4	36	474722665.4	13017.49524
East Staffordshire	2016	1	37	474709647.9	151699.5361
East Staffordshire	2016	2	38	474557948.4	159920.8122
East Staffordshire	2016	3	39	474398027.6	36284.43902
East Staffordshire	2016	4	40	474361743.1	12469.03132
East Staffordshire	2017	1	41	474349274.1	79917.10094
East Staffordshire	2017	2	42	474269357	145799.1654
East Staffordshire	2017	3	43	474123557.8	464176.941
East Staffordshire	2017	4	44	473659380.9	1343.796433
East Staffordshire	2018	1	45	473658037.1	254451.5554
East Staffordshire	2018	2	46	473403585.5	8435.007032
East Staffordshire	2018	3	47	473395150.5	126837.4125
East Staffordshire	2018	4	48	473268313.1	112738.114
Eden	2007	1	1	2090480154	2896.27
Eden	2007	2	2	2090477258	3121.52
Eden	2007	3	3	2090474136	4560
Eden	2007	4	4	2090469576	8725.6
Eden	2008	1	5	2090460851	14749.83
Eden	2008	2	6	2090446101	13662.2
Eden	2008	3	7	2090432439	0
Eden	2008	4	8	2090432439	15131.12
Eden	2009	1	9	2090417307	2337.91
Eden	2009	2	10	2090414970	1802.45
Eden	2009	3	11	2090413167	17107.12
Eden	2009	4	12	2090396060	13684.1
Eden	2010	1	13	2090382376	3790.89
Eden	2010	2	14	2090378585	0
Eden	2010	3	15	2090378585	0
Eden	2010	4	16	2090378585	0
Eden	2011	1	17	2090378585	0
Eden	2011	2	18	2090378585	6093.28
Eden	2011	3	19	2090372492	0
Eden	2011	4	20	2090372492	2573.37
Eden	2012	1	21	2090369918	0
Eden	2012	2	22	2090369918	20392.91
Eden	2012	3	23	2090349525	26678.89
Eden	2012	4	24	2090322847	0
Eden	2013	1	25	2090322847	2487.28
Eden	2013	2	26	2090320359	0
Eden	2013	3	27	2090320359	0
Eden	2013	4	28	2090320359	4796.99
Eden	2014	1	29	2090315562	10592.18
Eden	2014	2	30	2090304970	1523.16
Eden	2014	3	31	2090303447	2451.92
Eden	2014	4	32	2090300995	657.74
Eden	2015	1	33	2090300337	8379.28
Eden	2015	2	34	2090291958	43380.5
Eden	2015	3	35	2090248577	5258.36
Eden	2015	4	36	2090243319	5495.06

Eden	2016	1	37	2090237824	27302.61
Eden	2016	2	38	2090210521	35036.48
Eden	2016	3	39	2090175485	3085.32
Eden	2016	4	40	2090172400	5081.51
Eden	2017	1	41	2090167318	75616.42
Eden	2017	2	42	2090091702	11747.29
Eden	2017	3	43	2090079954	0
Eden	2017	4	44	2090079954	149736.96
Eden	2018	1	45	2089930217	139196.49
Eden	2018	2	46	2089791021	23.54
Eden	2018	3	47	2089790997	18212.92
Eden	2018	4	48	2089772785	547.91
Forest of Dean	2007	1	1	482607191	7327.006013
Forest of Dean	2007	2	2	482599864	4903.206555
Forest of Dean	2007	3	3	482594960.8	24210.21055
Forest of Dean	2007	4	4	482570750.6	9662.489382
Forest of Dean	2008	1	5	482561088.1	6131.140095
Forest of Dean	2008	2	6	482554957	10018.37261
Forest of Dean	2008	3	7	482544938.6	1041.923614
Forest of Dean	2008	4	8	482543896.7	0
Forest of Dean	2009	1	9	482543896.7	59.1976127
Forest of Dean	2009	2	10	482543837.5	4720.980533
Forest of Dean	2009	3	11	482539116.5	339.67185
Forest of Dean	2009	4	12	482538776.8	5454.709735
Forest of Dean	2010	1	13	482533322.1	1400.2539
Forest of Dean	2010	2	14	482531921.8	53060.80683
Forest of Dean	2010	3	15	482478861	0
Forest of Dean	2010	4	16	482478861	53760.7609
Forest of Dean	2011	1	17	482425100.3	501.3697544
Forest of Dean	2011	2	18	482424598.9	563.307734
Forest of Dean	2011	3	19	482424035.6	0.0029
Forest of Dean	2011	4	20	482424035.6	2788.490805
Forest of Dean	2012	1	21	482421247.1	95641.06829
Forest of Dean	2012	2	22	482325606	1489.089753
Forest of Dean	2012	3	23	482324116.9	16146.36369
Forest of Dean	2012	4	24	482307970.6	4688.340851
Forest of Dean	2013	1	25	482303282.2	537.649264
Forest of Dean	2013	2	26	482302744.6	5604.911268
Forest of Dean	2013	3	27	482297139.7	142.8707655
Forest of Dean	2013	4	28	482296996.8	20243.14347
Forest of Dean	2014	1	29	482276753.7	15523.18015
Forest of Dean	2014	2	30	482261230.5	21798.92163
Forest of Dean	2014	3	31	482239431.6	27807.62817
Forest of Dean	2014	4	32	482211623.9	34660.73302
Forest of Dean	2015	1	33	482176963.2	13855.1715
Forest of Dean	2015	2	34	482163108	5385.618657
Forest of Dean	2015	3	35	482157722.4	23184.98812
Forest of Dean	2015	4	36	482134537.4	19947.18351
Forest of Dean	2016	1	37	482114590.2	43248.07334
Forest of Dean	2016	2	38	482071342.2	8824.11166
Forest of Dean	2016	3	39	482062518.1	2523.167921
Forest of Dean	2016	4	40	482059994.9	72060.59627
Forest of Dean	2017	1	41	481987934.3	3677.720549
Forest of Dean	2017	2	42	481984256.6	109636.9554
Forest of Dean	2017	3	43	481874619.6	99996.88909
Forest of Dean	2017	4	44	481774622.7	2811.373772
Forest of Dean	2018	1	45	481771811.4	0
Forest of Dean	2018	2	46	481771811.4	0
Forest of Dean	2018	3	47	481771811.4	0
Forest of Dean	2018	4	48	481771811.4	170876.2782
Gedling	2007	1	1	91758914.66	0
Gedling	2007	2	2	91758914.66	18644.11259
Gedling	2007	3	3	91740270.55	15481.42648
Gedling	2007	4	4	91724789.12	23553.78315
Gedling	2008	1	5	91701235.34	39217.18705
Gedling	2008	2	6	91662018.15	56.25628988
Gedling	2008	3	7	91661961.89	2.015711173
Gedling	2008	4	8	91661959.88	1.622599617
Gedling	2009	1	9	91661958.26	11131.22841
Gedling	2009	2	10	91650827.03	0
Gedling	2009	3	11	91650827.03	163.5378365
Gedling	2009	4	12	91650663.49	2438.703839
Gedling	2010	1	13	91648224.79	19953.96151
Gedling	2010	2	14	91628270.82	1482.214925
Gedling	2010	3	15	91626788.61	1949.478052
Gedling	2010	4	16	91624839.13	42.58291855

Gedling	2011	1	17	91624796.55	2065.333047
Gedling	2011	2	18	91622731.22	0
Gedling	2011	3	19	91622731.22	58719.57902
Gedling	2011	4	20	91564011.64	40081.62505
Gedling	2012	1	21	91523930.01	2770.472802
Gedling	2012	2	22	91521159.54	44789.85746
Gedling	2012	3	23	91476369.68	64.20596101
Gedling	2012	4	24	91476305.48	2146.245537
Gedling	2013	1	25	91474159.23	5915.406831
Gedling	2013	2	26	91468243.82	18.30329384
Gedling	2013	3	27	91468225.52	56057.93808
Gedling	2013	4	28	91412167.58	108117.8814
Gedling	2014	1	29	91304049.7	1653.672522
Gedling	2014	2	30	91302396.03	6426.579232
Gedling	2014	3	31	91295969.45	922.4596739
Gedling	2014	4	32	91295046.99	228.6707566
Gedling	2015	1	33	91294818.32	0
Gedling	2015	2	34	91294818.32	0
Gedling	2015	3	35	91294818.32	0
Gedling	2015	4	36	91294818.32	28464.19892
Gedling	2016	1	37	91266354.12	0.0004
Gedling	2016	2	38	91266354.12	3191.675744
Gedling	2016	3	39	91263162.44	116417.2071
Gedling	2016	4	40	91146745.24	486.2668611
Gedling	2017	1	41	91146258.97	2699.82265
Gedling	2017	2	42	91143559.15	0
Gedling	2017	3	43	91143559.15	0
Gedling	2017	4	44	91143559.15	61809.97091
Gedling	2018	1	45	91081749.18	138378.2996
Gedling	2018	2	46	90943370.88	0
Gedling	2018	3	47	90943370.88	1520.92441
Gedling	2018	4	48	90941849.95	12467.32602
Harlow	2007	1	1	16214182.25	33043.6035
Harlow	2007	2	2	16181138.65	0
Harlow	2007	3	3	16181138.65	14289.94092
Harlow	2007	4	4	16166848.71	0
Harlow	2008	1	5	16166848.71	28.73981398
Harlow	2008	2	6	16166819.97	11929.10619
Harlow	2008	3	7	16154890.86	1297.948742
Harlow	2008	4	8	16153592.91	5278.86031
Harlow	2009	1	9	16148314.05	3182.68433
Harlow	2009	2	10	16145131.37	0
Harlow	2009	3	11	16145131.37	0
Harlow	2009	4	12	16145131.37	10610.78479
Harlow	2010	1	13	16134520.58	0
Harlow	2010	2	14	16134520.58	0
Harlow	2010	3	15	16134520.58	0
Harlow	2010	4	16	16134520.58	0
Harlow	2011	1	17	16134520.58	308.6316
Harlow	2011	2	18	16134211.95	0
Harlow	2011	3	19	16134211.95	0
Harlow	2011	4	20	16134211.95	0
Harlow	2012	1	21	16134211.95	0
Harlow	2012	2	22	16134211.95	587.8638456
Harlow	2012	3	23	16133624.09	0
Harlow	2012	4	24	16133624.09	0
Harlow	2013	1	25	16133624.09	0
Harlow	2013	2	26	16133624.09	7.59728829
Harlow	2013	3	27	16133616.49	248.6513181
Harlow	2013	4	28	16133367.84	0
Harlow	2014	1	29	16133367.84	0
Harlow	2014	2	30	16133367.84	17444.11641
Harlow	2014	3	31	16115923.72	247273.4389
Harlow	2014	4	32	15868650.28	2559.467672
Harlow	2015	1	33	15866090.81	0
Harlow	2015	2	34	15866090.81	0
Harlow	2015	3	35	15866090.81	10.64329513
Harlow	2015	4	36	15866080.17	0
Harlow	2016	1	37	15866080.17	17989.61455
Harlow	2016	2	38	15848090.56	9.82E-05
Harlow	2016	3	39	15848090.56	0
Harlow	2016	4	40	15848090.56	2212.729765
Harlow	2017	1	41	15845877.83	64763.85981
Harlow	2017	2	42	15781113.97	0
Harlow	2017	3	43	15781113.97	4574.743633
Harlow	2017	4	44	15776539.22	6228.270893

Harlow	2018	1	45	15770310.95	100.3730524
Harlow	2018	2	46	15770210.58	208999.6654
Harlow	2018	3	47	15561210.91	13506.07296
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Hart	2007	1	1	181128632.1	0
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Hart	2007	3	3	181126132.6	1841.25
Hart	2007	4	4	181124291.3	3.07
Hart	2008	1	5	181124288.2	5283.26
Hart	2008	2	6	181119005	0
Hart	2008	3	7	181119005	688.1
Hart	2008	4	8	181118316.9	0
Hart	2009	1	9	181118316.9	3347.75
Hart	2009	2	10	181114969.1	0
Hart	2009	3	11	181114969.1	0
Hart	2009	4	12	181114969.1	0
Hart	2010	1	13	181114969.1	0
Hart	2010	2	14	181114969.1	0
Hart	2010	3	15	181114969.1	32124.41
Hart	2010	4	16	181082844.7	372.33
Hart	2011	1	17	181082472.4	79661.84
Hart	2011	2	18	181002810.6	15029.82
Hart	2011	3	19	180987780.7	86599.74
Hart	2011	4	20	180901181	288.11
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Hart	2012	2	22	180900487.4	1351.26
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Hart	2012	4	24	180895616.1	5156.99
Hart	2013	1	25	180890459.1	4.39
Hart	2013	2	26	180890454.7	4067.92
Hart	2013	3	27	180886386.8	8678.01
Hart	2013	4	28	180877708.8	22015.07
Hart	2014	1	29	180855693.7	11667.29
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Hart	2014	3	31	180757325.8	27181.88
Hart	2014	4	32	180730143.9	64049.76
Hart	2015	1	33	180666094.1	4652.28
Hart	2015	2	34	180661441.8	32710.44
Hart	2015	3	35	180628731.4	72785.18
Hart	2015	4	36	180555946.2	0
Hart	2016	1	37	180555946.2	71989.87
Hart	2016	2	38	180483956.4	17719.89
Hart	2016	3	39	180466236.5	15978.88
Hart	2016	4	40	180450257.6	1208.67
Hart	2017	1	41	180449048.9	93410.06
Hart	2017	2	42	180355638.8	229.73
Hart	2017	3	43	180355409.1	3.81
Hart	2017	4	44	180355405.3	829.95
Hart	2018	1	45	180354575.4	6022.5
Hart	2018	2	46	180348552.9	2068.95
Hart	2018	3	47	180346483.9	27304.23
Hart	2018	4	48	180319179.7	107651.86
Hastings	2007	1	1	14151481	0
Hastings	2007	2	2	14151481	10782.33247
Hastings	2007	3	3	14140698.67	0
Hastings	2007	4	4	14140698.67	3606.987092
Hastings	2008	1	5	14137091.68	620.5978456
Hastings	2008	2	6	14136471.08	10853.44619
Hastings	2008	3	7	14125617.64	100.5584971
Hastings	2008	4	8	14125517.08	3341.087706
Hastings	2009	1	9	14122175.99	795.306696
Hastings	2009	2	10	14121380.68	11105.7485
Hastings	2009	3	11	14110274.93	0
Hastings	2009	4	12	14110274.93	0.413149752
Hastings	2010	1	13	14110274.52	13786.72473
Hastings	2010	2	14	14096487.8	10543.85704
Hastings	2010	3	15	14085943.94	0
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Hastings	2011	1	17	14083986.86	0
Hastings	2011	2	18	14083986.86	0.0818
Hastings	2011	3	19	14083986.78	171.85084
Hastings	2011	4	20	14083814.92	545.892871
Hastings	2012	1	21	14083269.03	0
Hastings	2012	2	22	14083269.03	0
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Hastings	2013	1	25	14071031.88	412.2520593
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Hastings	2014	2	30	14033545.21	0
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Hastings	2015	1	33	13992642.44	7060.598657
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Hastings	2017	1	41	13931110.98	4504.201224
Hastings	2017	2	42	13926606.78	0
Hastings	2017	3	43	13926606.78	676.0747408
Hastings	2017	4	44	13925930.7	0
Hastings	2018	1	45	13925930.7	4136.87349
Hastings	2018	2	46	13921793.83	4317.756448
Hastings	2018	3	47	13917476.07	237.7065337
Hastings	2018	4	48	13917238.37	0.495900669
Herefordshire, County of	2007	1	1	2076186089	12960.41481
Herefordshire, County of	2007	2	2	2076173129	38161.79625
Herefordshire, County of	2007	3	3	2076134967	29603.42828
Herefordshire, County of	2007	4	4	2076105363	57389.89916
Herefordshire, County of	2008	1	5	2076047973	51186.59886
Herefordshire, County of	2008	2	6	2075996787	18175.43513
Herefordshire, County of	2008	3	7	2075978611	19386.88275
Herefordshire, County of	2008	4	8	2075959225	45387.99632
Herefordshire, County of	2009	1	9	2075913837	7019.099738
Herefordshire, County of	2009	2	10	2075906817	4840.613366
Herefordshire, County of	2009	3	11	2075901977	2039.808507
Herefordshire, County of	2009	4	12	2075899937	28310.87389
Herefordshire, County of	2010	1	13	2075871626	8486.59304
Herefordshire, County of	2010	2	14	2075863140	12802.8855
Herefordshire, County of	2010	3	15	2075850337	25006.97817
Herefordshire, County of	2010	4	16	2075825330	53106.84019
Herefordshire, County of	2011	1	17	2075772223	75484.04594
Herefordshire, County of	2011	2	18	2075696739	10066.39611
Herefordshire, County of	2011	3	19	2075686672	1890.4285
Herefordshire, County of	2011	4	20	2075684782	46825.45748
Herefordshire, County of	2012	1	21	2075637957	52177.92929
Herefordshire, County of	2012	2	22	2075585779	15926.4415
Herefordshire, County of	2012	3	23	2075569852	875.7419876
Herefordshire, County of	2012	4	24	2075568976	5428.31864
Herefordshire, County of	2013	1	25	2075563548	9831.501249
Herefordshire, County of	2013	2	26	2075553717	151.115072
Herefordshire, County of	2013	3	27	2075553565	0
Herefordshire, County of	2013	4	28	2075553565	9145.247774
Herefordshire, County of	2014	1	29	2075544420	53691.29961
Herefordshire, County of	2014	2	30	2075490729	30414.92218
Herefordshire, County of	2014	3	31	2075460314	37114.58684
Herefordshire, County of	2014	4	32	2075423199	1377.712574
Herefordshire, County of	2015	1	33	2075421822	9035.680642
Herefordshire, County of	2015	2	34	2075412786	40703.63329
Herefordshire, County of	2015	3	35	2075372082	4599.938878
Herefordshire, County of	2015	4	36	2075367482	17750.17334
Herefordshire, County of	2016	1	37	2075349732	28982.70272
Herefordshire, County of	2016	2	38	2075320750	21637.11243
Herefordshire, County of	2016	3	39	2075299112	72134.28095
Herefordshire, County of	2016	4	40	2075226978	28873.49815
Herefordshire, County of	2017	1	41	2075198105	134770.3812
Herefordshire, County of	2017	2	42	2075063334	33428.25978
Herefordshire, County of	2017	3	43	2075029906	302679.0429
Herefordshire, County of	2017	4	44	2074727227	53880.35663
Herefordshire, County of	2018	1	45	2074673347	70730.0801
Herefordshire, County of	2018	2	46	2074602617	20411.84255
Herefordshire, County of	2018	3	47	2074582205	66854.83863
Herefordshire, County of	2018	4	48	2074515350	181659.9614
Kingston upon Hull, City of	2007	1	1	24251344.71	13.59285104
Kingston upon Hull, City of	2007	2	2	24251331.12	33207.57299
Kingston upon Hull, City of	2007	3	3	24218123.54	307.2751088
Kingston upon Hull, City of	2007	4	4	24217816.27	13110.95481

Kingston upon Hull, City of	2008	1	5	24204705.31	21412.05344
Kingston upon Hull, City of	2008	2	6	24183293.26	1855.924298
Kingston upon Hull, City of	2008	3	7	24181437.34	31346.82103
Kingston upon Hull, City of	2008	4	8	24150090.52	131.894616
Kingston upon Hull, City of	2009	1	9	24149958.62	23421.88948
Kingston upon Hull, City of	2009	2	10	24126536.73	0
Kingston upon Hull, City of	2009	3	11	24126536.73	29.82911333
Kingston upon Hull, City of	2009	4	12	24126506.9	1826.21235
Kingston upon Hull, City of	2010	1	13	24124680.69	28362.84067
Kingston upon Hull, City of	2010	2	14	24096317.85	0
Kingston upon Hull, City of	2010	3	15	24096317.85	0
Kingston upon Hull, City of	2010	4	16	24096317.85	10051.6211
Kingston upon Hull, City of	2011	1	17	24086266.23	44328.36327
Kingston upon Hull, City of	2011	2	18	24041937.86	12192.93082
Kingston upon Hull, City of	2011	3	19	24029744.93	94505.29298
Kingston upon Hull, City of	2011	4	20	23935239.64	77246.5866
Kingston upon Hull, City of	2012	1	21	23857993.05	83901.48363
Kingston upon Hull, City of	2012	2	22	23774091.57	26120.7474
Kingston upon Hull, City of	2012	3	23	23747970.82	44504.11201
Kingston upon Hull, City of	2012	4	24	23703466.71	1.859442569
Kingston upon Hull, City of	2013	1	25	23703464.85	12400.9092
Kingston upon Hull, City of	2013	2	26	23691063.94	11533.82237
Kingston upon Hull, City of	2013	3	27	23679530.12	41471.78911
Kingston upon Hull, City of	2013	4	28	23638058.33	3671.013822
Kingston upon Hull, City of	2014	1	29	23634387.32	7608.355342
Kingston upon Hull, City of	2014	2	30	23626778.96	7024.429864
Kingston upon Hull, City of	2014	3	31	23619754.53	25668.00848
Kingston upon Hull, City of	2014	4	32	23594086.52	86733.50759
Kingston upon Hull, City of	2015	1	33	23507353.02	814.4651131
Kingston upon Hull, City of	2015	2	34	23506538.55	12001.03722
Kingston upon Hull, City of	2015	3	35	23494537.51	112292.0944
Kingston upon Hull, City of	2015	4	36	23382245.42	13310.77616
Kingston upon Hull, City of	2016	1	37	23368934.64	2141.28341
Kingston upon Hull, City of	2016	2	38	23366793.36	0
Kingston upon Hull, City of	2016	3	39	23366793.36	5641.285557
Kingston upon Hull, City of	2016	4	40	23361152.07	88317.90719

Table B.1: Babergh - Kingston upon Hull Q4 2016

Kingston upon Hull, City of	2017	1	41	23272834.17	93647.87634
Kingston upon Hull, City of	2017	2	42	23179186.29	17690.16059
Kingston upon Hull, City of	2017	3	43	23161496.13	5535.957024
Kingston upon Hull, City of	2017	4	44	23155960.17	2409.037989
Kingston upon Hull, City of	2018	1	45	23153551.14	7960.398722
Kingston upon Hull, City of	2018	2	46	23145590.74	90677.85943
Kingston upon Hull, City of	2018	3	47	23054912.88	35061.63688
Kingston upon Hull, City of	2018	4	48	23019851.24	12642.41002
Leeds	2007	1	1	389703729	376745.865
Leeds	2007	2	2	389326983.1	8795.335823
Leeds	2007	3	3	389318187.8	19001.62568
Leeds	2007	4	4	389299186.2	55774.44058
Leeds	2008	1	5	389243411.7	533529.3136
Leeds	2008	2	6	388709882.4	39294.30072
Leeds	2008	3	7	388670588.1	8181.184914
Leeds	2008	4	8	388662406.9	19536.05141
Leeds	2009	1	9	388642870.9	53176.37063
Leeds	2009	2	10	388589694.5	2608.01015
Leeds	2009	3	11	388587086.5	3104.872183
Leeds	2009	4	12	388583981.6	32716.14342
Leeds	2010	1	13	388551265.5	29092.93622
Leeds	2010	2	14	388522172.6	57298.31878
Leeds	2010	3	15	388464874.2	16936.02462
Leeds	2010	4	16	388447938.2	5764.681349
Leeds	2011	1	17	388442173.5	6126.911071
Leeds	2011	2	18	388436046.6	14625.03868
Leeds	2011	3	19	388421421.6	6227.516057
Leeds	2011	4	20	388415194.1	23815.86972
Leeds	2012	1	21	388391378.2	18019.29343
Leeds	2012	2	22	388373358.9	30521.61416
Leeds	2012	3	23	388342837.3	8753.711413
Leeds	2012	4	24	388334083.6	111326.3459
Leeds	2013	1	25	388222757.2	20976.39498
Leeds	2013	2	26	388201780.8	44448.42034
Leeds	2013	3	27	388157332.4	23218.82801

Leeds	2013	4	28	388134113.6	147468.2957
Leeds	2014	1	29	387986645.3	9198.585084
Leeds	2014	2	30	387977446.7	87894.88603
Leeds	2014	3	31	387889551.8	63444.46637
Leeds	2014	4	32	387826107.4	80170.82945
Leeds	2015	1	33	387745936.5	85410.25434
Leeds	2015	2	34	387660526.3	207714.4393
Leeds	2015	3	35	387452811.8	101046.2359
Leeds	2015	4	36	387351765.6	71124.07184
Leeds	2016	1	37	387280641.5	85660.95986
Leeds	2016	2	38	387194980.6	38278.64622
Leeds	2016	3	39	387156701.9	175152.8141
Leeds	2016	4	40	386981549.1	404981.4751
Leeds	2017	1	41	386576567.6	36206.96407
Leeds	2017	2	42	386540360.7	229235.1043
Leeds	2017	3	43	386311125.6	528642.0877
Leeds	2017	4	44	385782483.5	26880.75691
Leeds	2018	1	45	385755602.7	84378.25699
Leeds	2018	2	46	385671224.5	101977.6893
Leeds	2018	3	47	385569246.8	141582.6536
Leeds	2018	4	48	385427664.1	656079.8592
North Tyneside	2007	1	1	45035882.81	3061.69
North Tyneside	2007	2	2	45032821.12	5306.23
North Tyneside	2007	3	3	45027514.89	41780.16
North Tyneside	2007	4	4	44985734.72	12359.5
North Tyneside	2008	1	5	44973375.22	101002.86
North Tyneside	2008	2	6	44872372.36	43446.47
North Tyneside	2008	3	7	44828925.89	27402.57
North Tyneside	2008	4	8	44801523.32	73407.07
North Tyneside	2009	1	9	44728116.25	0
North Tyneside	2009	2	10	44728116.25	1713.19
North Tyneside	2009	3	11	44726403.06	0
North Tyneside	2009	4	12	44726403.06	22760.91
North Tyneside	2010	1	13	44703642.15	0
North Tyneside	2010	2	14	44703642.15	16865.86
North Tyneside	2010	3	15	44686776.29	5298.4
North Tyneside	2010	4	16	44681477.89	632.84
North Tyneside	2011	1	17	44680845.05	21011.98
North Tyneside	2011	2	18	44659833.07	2.17
North Tyneside	2011	3	19	44659830.9	71.68
North Tyneside	2011	4	20	44659759.22	4318.75
North Tyneside	2012	1	21	44655440.47	14586.12
North Tyneside	2012	2	22	44640854.36	0
North Tyneside	2012	3	23	44640854.36	0
North Tyneside	2012	4	24	44640854.36	524.73
North Tyneside	2013	1	25	44640329.63	96603.53
North Tyneside	2013	2	26	44543726.1	35198.06
North Tyneside	2013	3	27	44508528.05	223.04
North Tyneside	2013	4	28	44508305.01	87795.63
North Tyneside	2014	1	29	44420509.38	0
North Tyneside	2014	2	30	44420509.38	2166.89
North Tyneside	2014	3	31	44418342.48	113406.25
North Tyneside	2014	4	32	44304936.24	5386.65
North Tyneside	2015	1	33	44299549.59	16903.28
North Tyneside	2015	2	34	44282646.31	21943.39
North Tyneside	2015	3	35	44260702.92	901.06
North Tyneside	2015	4	36	44259801.86	79341.79
North Tyneside	2016	1	37	44180460.07	3215.31
North Tyneside	2016	2	38	44177244.76	167304.06
North Tyneside	2016	3	39	44009940.7	362368.58
North Tyneside	2016	4	40	43647572.12	162816.49
North Tyneside	2017	1	41	43484755.63	8697
North Tyneside	2017	2	42	43476058.63	10647.19
North Tyneside	2017	3	43	43465411.44	1865.15
North Tyneside	2017	4	44	43463546.29	233217.21
North Tyneside	2018	1	45	43230329.08	28052.44
North Tyneside	2018	2	46	43202276.64	2558.01
North Tyneside	2018	3	47	43199718.63	100290.16
North Tyneside	2018	4	48	43099428.47	103964.87
North Warwickshire	2007	1	1	250496275.5	16.89335709
North Warwickshire	2007	2	2	250496258.6	0
North Warwickshire	2007	3	3	250496258.6	0
North Warwickshire	2007	4	4	250496258.6	0
North Warwickshire	2008	1	5	250496258.6	3610.15739
North Warwickshire	2008	2	6	250492648.5	0
North Warwickshire	2008	3	7	250492648.5	40899.75382

North Warwickshire	2008	4	8	250451748.7	4613.51755
North Warwickshire	2009	1	9	250447135.2	3159.806653
North Warwickshire	2009	2	10	250443975.4	0
North Warwickshire	2009	3	11	250443975.4	0
North Warwickshire	2009	4	12	250443975.4	0
North Warwickshire	2010	1	13	250443975.4	145.5941463
North Warwickshire	2010	2	14	250443829.8	0
North Warwickshire	2010	3	15	250443829.8	134.1296685
North Warwickshire	2010	4	16	250443695.7	0
North Warwickshire	2011	1	17	250443695.7	7.965360696
North Warwickshire	2011	2	18	250443687.7	0
North Warwickshire	2011	3	19	250443687.7	2809.802284
North Warwickshire	2011	4	20	250440877.9	0
North Warwickshire	2012	1	21	250440877.9	424295.4866
North Warwickshire	2012	2	22	250016582.4	0
North Warwickshire	2012	3	23	250016582.4	0
North Warwickshire	2012	4	24	250016582.4	0
North Warwickshire	2013	1	25	250016582.4	0
North Warwickshire	2013	2	26	250016582.4	297.9539563
North Warwickshire	2013	3	27	250016284.4	4610.204157
North Warwickshire	2013	4	28	250011674.2	5518.782708
North Warwickshire	2014	1	29	250006155.5	25091.31168
North Warwickshire	2014	2	30	249981064.1	18077.22375
North Warwickshire	2014	3	31	249962986.9	23589.08642
North Warwickshire	2014	4	32	249939397.8	1932.742216
North Warwickshire	2015	1	33	249937465.1	4036.619905
North Warwickshire	2015	2	34	249933428.5	5224.610828
North Warwickshire	2015	3	35	249928203.9	851.0547778
North Warwickshire	2015	4	36	249927352.8	6899.102961
North Warwickshire	2016	1	37	249920453.7	132140.4164
North Warwickshire	2016	2	38	249788313.3	9286.677939
North Warwickshire	2016	3	39	249779026.6	111387.5539
North Warwickshire	2016	4	40	249667639.1	29496.82807
North Warwickshire	2017	1	41	249638142.2	16623.3124
North Warwickshire	2017	2	42	249621518.9	11930.36935
North Warwickshire	2017	3	43	249609588.5	97549.10598
North Warwickshire	2017	4	44	249512039.4	7220.076985
North Warwickshire	2018	1	45	249504819.4	20913.37658
North Warwickshire	2018	2	46	249483906	3.69E-09
North Warwickshire	2018	3	47	249483906	0.005304053
North Warwickshire	2018	4	48	249483906	9640.421797
Norwich	2007	1	1	13867451.82	0
Norwich	2007	2	2	13867451.82	1297.85491
Norwich	2007	3	3	13866153.97	0
Norwich	2007	4	4	13866153.97	219.0473186
Norwich	2008	1	5	13865934.92	9606.217894
Norwich	2008	2	6	13856328.7	4761.192394
Norwich	2008	3	7	13851567.51	3567.022229
Norwich	2008	4	8	13848000.49	4951.172483
Norwich	2009	1	9	13843049.31	2182.44385
Norwich	2009	2	10	13840866.87	1220.233106
Norwich	2009	3	11	13839646.64	0
Norwich	2009	4	12	13839646.64	0
Norwich	2010	1	13	13839646.64	1481.898267
Norwich	2010	2	14	13838164.74	228.9547596
Norwich	2010	3	15	13837935.78	1848.786168
Norwich	2010	4	16	13836087	0
Norwich	2011	1	17	13836087	6.6518
Norwich	2011	2	18	13836080.34	9479.127892
Norwich	2011	3	19	13826601.22	0
Norwich	2011	4	20	13826601.22	0
Norwich	2012	1	21	13826601.22	0
Norwich	2012	2	22	13826601.22	201.933435
Norwich	2012	3	23	13826399.28	70.841108
Norwich	2012	4	24	13826328.44	62.492272
Norwich	2013	1	25	13826265.95	403.6002255
Norwich	2013	2	26	13825862.35	3306.860839
Norwich	2013	3	27	13822555.49	6833.336611
Norwich	2013	4	28	13815722.15	0
Norwich	2014	1	29	13815722.15	2.330519454
Norwich	2014	2	30	13815719.82	0
Norwich	2014	3	31	13815719.82	6.736985
Norwich	2014	4	32	13815713.08	35639.42583
Norwich	2015	1	33	13780073.66	3049.54386
Norwich	2015	2	34	13777024.12	17257.1413
Norwich	2015	3	35	13759766.97	49320.43297

Norwich	2015	4	36	13710446.54	6564.731688
Norwich	2016	1	37	13703881.81	22175.20578
Norwich	2016	2	38	13681706.6	471.0478267
Norwich	2016	3	39	13681235.56	8631.009675
Norwich	2016	4	40	13672604.55	77634.4455
Norwich	2017	1	41	13594970.1	5905.994529
Norwich	2017	2	42	13589064.11	664.6411676
Norwich	2017	3	43	13588399.46	0
Norwich	2017	4	44	13588399.46	81.08230756
Norwich	2018	1	45	13588318.38	0
Norwich	2018	2	46	13588318.38	27372.20405
Norwich	2018	3	47	13560946.18	280.1394296
Norwich	2018	4	48	13560666.04	6809.493893
Oldham	2007	1	1	90741897.73	0
Oldham	2007	2	2	90741897.73	0
Oldham	2007	3	3	90741897.73	652.3242071
Oldham	2007	4	4	90741245.41	3892.245105
Oldham	2008	1	5	90737353.16	8313.172128
Oldham	2008	2	6	90729039.99	4198.059611
Oldham	2008	3	7	90724841.93	21703.92646
Oldham	2008	4	8	90703138	15990.19428
Oldham	2009	1	9	90687147.81	3302.363897
Oldham	2009	2	10	90683845.44	0
Oldham	2009	3	11	90683845.44	1.448033324
Oldham	2009	4	12	90683844	4362.085023
Oldham	2010	1	13	90679481.91	31.94796381
Oldham	2010	2	14	90679449.96	252.1078162
Oldham	2010	3	15	90679197.86	0
Oldham	2010	4	16	90679197.86	0
Oldham	2011	1	17	90679197.86	1625.031444
Oldham	2011	2	18	90677572.82	0
Oldham	2011	3	19	90677572.82	0
Oldham	2011	4	20	90677572.82	2238.961817
Oldham	2012	1	21	90675333.86	0
Oldham	2012	2	22	90675333.86	1950.367095
Oldham	2012	3	23	90673383.5	3724.064265
Oldham	2012	4	24	90669659.43	0
Oldham	2013	1	25	90669659.43	397.8940207
Oldham	2013	2	26	90669261.54	0
Oldham	2013	3	27	90669261.54	115.2945541
Oldham	2013	4	28	90669146.24	922.3304753
Oldham	2014	1	29	90668223.91	15.22772096
Oldham	2014	2	30	90668208.68	5169.863563
Oldham	2014	3	31	90663038.82	3884.383882
Oldham	2014	4	32	90659154.44	7540.626214
Oldham	2015	1	33	90651613.81	251.4082772
Oldham	2015	2	34	90651362.4	4111.280097
Oldham	2015	3	35	90647251.12	3795.46061
Oldham	2015	4	36	90643455.66	0
Oldham	2016	1	37	90643455.66	1402.160859
Oldham	2016	2	38	90642053.5	15088.82723
Oldham	2016	3	39	90626964.67	18012.07764
Oldham	2016	4	40	90608952.6	2889.047318
Oldham	2017	1	41	90606063.55	12996.47935
Oldham	2017	2	42	90593067.07	5772.827452
Oldham	2017	3	43	90587294.24	926.5907459
Oldham	2017	4	44	90586367.65	403.7606959
Oldham	2018	1	45	90585963.89	3025.428771
Oldham	2018	2	46	90582938.46	38248.95092
Oldham	2018	3	47	90544689.51	627.8469994
Oldham	2018	4	48	90544061.66	23174.03266
Pendle	2007	1	1	148508150.4	22306.29759
Pendle	2007	2	2	148485844.1	146.5130071
Pendle	2007	3	3	148485697.6	0
Pendle	2007	4	4	148485697.6	0
Pendle	2008	1	5	148485697.6	3237.90033
Pendle	2008	2	6	148482459.7	2509.87694
Pendle	2008	3	7	148479949.8	48757.09896
Pendle	2008	4	8	148431192.7	7809.638308
Pendle	2009	1	9	148423383.1	11979.37113
Pendle	2009	2	10	148411403.7	0
Pendle	2009	3	11	148411403.7	26927.94372
Pendle	2009	4	12	148384475.8	32190.72675
Pendle	2010	1	13	148352285	2008.044538
Pendle	2010	2	14	148350277	166.1806
Pendle	2010	3	15	148350110.8	73.69455574

Pendle	2010	4	16	148350037.1	42972.86272
Pendle	2011	1	17	148307064.3	12274.47373
Pendle	2011	2	18	148294789.8	0
Pendle	2011	3	19	148294789.8	0
Pendle	2011	4	20	148294789.8	0
Pendle	2012	1	21	148294789.8	0
Pendle	2012	2	22	148294789.8	0.0000586
Pendle	2012	3	23	148294789.8	1717.600994
Pendle	2012	4	24	148293072.2	0
Pendle	2013	1	25	148293072.2	0
Pendle	2013	2	26	148293072.2	0
Pendle	2013	3	27	148293072.2	0
Pendle	2013	4	28	148293072.2	9.16024081
Pendle	2014	1	29	148293063	0.011968233
Pendle	2014	2	30	148293063	1177.154136
Pendle	2014	3	31	148291885.9	791.791091
Pendle	2014	4	32	148291094.1	1780.109793
Pendle	2015	1	33	148289314	75.98334485
Pendle	2015	2	34	148289238	1284.308762
Pendle	2015	3	35	148287953.7	7047.308634
Pendle	2015	4	36	148280906.4	2686.84891
Pendle	2016	1	37	148278219.5	1932.592633
Pendle	2016	2	38	148276286.9	0.004449066
Pendle	2016	3	39	148276286.9	0
Pendle	2016	4	40	148276286.9	10879.94707
Pendle	2017	1	41	148265407	0
Pendle	2017	2	42	148265407	0
Pendle	2017	3	43	148265407	3211.480112
Pendle	2017	4	44	148262195.5	10911.78257
Pendle	2018	1	45	148251283.7	0
Pendle	2018	2	46	148251283.7	8599.386774
Pendle	2018	3	47	148242684.3	15197.57682
Pendle	2018	4	48	148227486.7	5475.789117
Plymouth	2007	1	1	35156315.24	2777.333584
Plymouth	2007	2	2	35153537.91	6.199687451
Plymouth	2007	3	3	35153531.71	2036.143401
Plymouth	2007	4	4	35151495.56	627.0685643
Plymouth	2008	1	5	35150868.49	8903.729129
Plymouth	2008	2	6	35141964.77	682.4285751
Plymouth	2008	3	7	35141282.34	7162.4059
Plymouth	2008	4	8	35134119.93	22995.0243
Plymouth	2009	1	9	35111124.91	1693.376079
Plymouth	2009	2	10	35109431.53	3033.763404
Plymouth	2009	3	11	35106397.77	31481.02725
Plymouth	2009	4	12	35074916.74	5416.034995
Plymouth	2010	1	13	35069500.71	11041.86608
Plymouth	2010	2	14	35058458.84	19167.83443
Plymouth	2010	3	15	35039291	21783.26833
Plymouth	2010	4	16	35017507.74	3438.395302
Plymouth	2011	1	17	35014069.34	1314.01315
Plymouth	2011	2	18	35012755.33	3475.224079
Plymouth	2011	3	19	35009280.1	23040.75124
Plymouth	2011	4	20	34986239.35	6588.043638
Plymouth	2012	1	21	34979651.31	0
Plymouth	2012	2	22	34979651.31	12031.92717
Plymouth	2012	3	23	34967619.38	16614.62499
Plymouth	2012	4	24	34951004.76	13278.05959
Plymouth	2013	1	25	34937726.7	3.386438971
Plymouth	2013	2	26	34937723.31	1202.162828
Plymouth	2013	3	27	34936521.15	16623.63755
Plymouth	2013	4	28	34919897.51	12160.86265
Plymouth	2014	1	29	34907736.65	17622.99947
Plymouth	2014	2	30	34890113.65	7120.971374
Plymouth	2014	3	31	34882992.68	23477.97725
Plymouth	2014	4	32	34859514.7	11605.56501
Plymouth	2015	1	33	34847909.13	97.06908538
Plymouth	2015	2	34	34847812.07	8342.541944
Plymouth	2015	3	35	34839469.52	56082.40492
Plymouth	2015	4	36	34783387.12	34944.68889
Plymouth	2016	1	37	34748442.43	1811.657838
Plymouth	2016	2	38	34746630.77	24590.09673
Plymouth	2016	3	39	34722040.68	40937.31263
Plymouth	2016	4	40	34681103.36	3898.496373
Plymouth	2017	1	41	34677204.87	1551.440578
Plymouth	2017	2	42	34675653.43	62197.18605
Plymouth	2017	3	43	34613456.24	19330.14837

Plymouth	2017	4	44	34594126.09	316429.6371
Plymouth	2018	1	45	34277696.45	34846.60885
Plymouth	2018	2	46	34242849.85	46410.61921
Plymouth	2018	3	47	34196439.23	35067.12916
Plymouth	2018	4	48	34161372.1	46537.53905
Portsmouth	2007	1	1	13458887.74	0
Portsmouth	2007	2	2	13458887.74	554.19875
Portsmouth	2007	3	3	13458333.54	836.02135
Portsmouth	2007	4	4	13457497.52	0
Portsmouth	2008	1	5	13457497.52	0
Portsmouth	2008	2	6	13457497.52	0
Portsmouth	2008	3	7	13457497.52	0.314688293
Portsmouth	2008	4	8	13457497.21	14.74451845
Portsmouth	2009	1	9	13457482.46	0
Portsmouth	2009	2	10	13457482.46	0.00062517
Portsmouth	2009	3	11	13457482.46	0
Portsmouth	2009	4	12	13457482.46	767.4582068
Portsmouth	2010	1	13	13456715	0
Portsmouth	2010	2	14	13456715	0
Portsmouth	2010	3	15	13456715	0
Portsmouth	2010	4	16	13456715	0
Portsmouth	2011	1	17	13456715	0
Portsmouth	2011	2	18	13456715	9243.195381
Portsmouth	2011	3	19	13447471.81	557.8633992
Portsmouth	2011	4	20	13446913.94	0
Portsmouth	2012	1	21	13446913.94	0
Portsmouth	2012	2	22	13446913.94	3402.732248
Portsmouth	2012	3	23	13443511.21	12709.72239
Portsmouth	2012	4	24	13430801.49	195.92045
Portsmouth	2013	1	25	13430605.57	0
Portsmouth	2013	2	26	13430605.57	0
Portsmouth	2013	3	27	13430605.57	1096.307735
Portsmouth	2013	4	28	13429509.26	22697.03831
Portsmouth	2014	1	29	13406812.22	0.000538972
Portsmouth	2014	2	30	13406812.22	186.0201685
Portsmouth	2014	3	31	13406626.2	0
Portsmouth	2014	4	32	13406626.2	0
Portsmouth	2015	1	33	13406626.2	0
Portsmouth	2015	2	34	13406626.2	0
Portsmouth	2015	3	35	13406626.2	562.0448343
Portsmouth	2015	4	36	13406064.16	0
Portsmouth	2016	1	37	13406064.16	0
Portsmouth	2016	2	38	13406064.16	0.662358518
Portsmouth	2016	3	39	13406063.49	682.364958
Portsmouth	2016	4	40	13405381.13	3614.679993
Portsmouth	2017	1	41	13401766.45	0
Portsmouth	2017	2	42	13401766.45	0
Portsmouth	2017	3	43	13401766.45	3531.691167
Portsmouth	2017	4	44	13398234.76	369.7217695
Portsmouth	2018	1	45	13397865.04	0
Portsmouth	2018	2	46	13397865.04	0
Portsmouth	2018	3	47	13397865.04	0
Portsmouth	2018	4	48	13397865.04	0
Redcar and Cleveland	2007	1	1	207165207.1	8441.488317
Redcar and Cleveland	2007	2	2	207156765.6	26924.2232
Redcar and Cleveland	2007	3	3	207129841.4	13256.83145
Redcar and Cleveland	2007	4	4	207116584.6	29455.63601
Redcar and Cleveland	2008	1	5	207087128.9	15445.72732
Redcar and Cleveland	2008	2	6	207071683.2	1148.32335
Redcar and Cleveland	2008	3	7	207070534.9	6629.645646
Redcar and Cleveland	2008	4	8	207063905.2	15601.15321
Redcar and Cleveland	2009	1	9	207048304.1	14754.56713
Redcar and Cleveland	2009	2	10	207033549.5	670.3025209
Redcar and Cleveland	2009	3	11	207032879.2	6163.47755
Redcar and Cleveland	2009	4	12	207026715.7	777.7416856
Redcar and Cleveland	2010	1	13	207025938	21555.13157
Redcar and Cleveland	2010	2	14	207004382.9	15160.63892
Redcar and Cleveland	2010	3	15	206989222.2	16659.54783
Redcar and Cleveland	2010	4	16	206972562.7	7886.94608
Redcar and Cleveland	2011	1	17	206964675.7	18908.31657
Redcar and Cleveland	2011	2	18	206945767.4	5876.873996
Redcar and Cleveland	2011	3	19	206939890.5	2009.849856
Redcar and Cleveland	2011	4	20	206937880.7	40892.22815
Redcar and Cleveland	2012	1	21	206896988.5	786.9722695
Redcar and Cleveland	2012	2	22	206896201.5	56699.1287
Redcar and Cleveland	2012	3	23	206839502.4	464.8712892

Redcar and Cleveland	2012	4	24	206839037.5	8328.300805
Redcar and Cleveland	2013	1	25	206830709.2	40966.65541
Redcar and Cleveland	2013	2	26	206789742.5	1928.314797
Redcar and Cleveland	2013	3	27	206787814.2	8974.517301
Redcar and Cleveland	2013	4	28	206778839.7	20271.09902
Redcar and Cleveland	2014	1	29	206758568.6	34224.11406
Redcar and Cleveland	2014	2	30	206724344.5	44244.58394
Redcar and Cleveland	2014	3	31	206680099.9	5699.768239
Redcar and Cleveland	2014	4	32	206674400.1	5.5049747
Redcar and Cleveland	2015	1	33	206674394.6	24296.1439
Redcar and Cleveland	2015	2	34	206650098.5	1218.281532
Redcar and Cleveland	2015	3	35	206648880.2	116017.6769
Redcar and Cleveland	2015	4	36	206532862.5	45873.8005
Redcar and Cleveland	2016	1	37	206486988.7	25593.4435
Redcar and Cleveland	2016	2	38	206461395.3	61531.51338
Redcar and Cleveland	2016	3	39	206399863.8	57294.29656
Redcar and Cleveland	2016	4	40	206342569.5	111550.4046
Redcar and Cleveland	2017	1	41	206231019.1	64922.10327
Redcar and Cleveland	2017	2	42	206166097	59028.36258
Redcar and Cleveland	2017	3	43	206107068.6	41774.37359
Redcar and Cleveland	2017	4	44	206065294.2	30252.45836
Redcar and Cleveland	2018	1	45	206035041.8	465.231524
Redcar and Cleveland	2018	2	46	206034576.5	16931.90351
Redcar and Cleveland	2018	3	47	206017644.6	9271.013616
Redcar and Cleveland	2018	4	48	206008373.6	67101.87139
Rossendale	2007	1	1	121292776	3893.122408
Rossendale	2007	2	2	121288882.9	883.1363712
Rossendale	2007	3	3	121287999.7	737.4406005
Rossendale	2007	4	4	121287262.3	21748.49987
Rossendale	2008	1	5	121265513.8	2966.389201
Rossendale	2008	2	6	121262547.4	6737.088059
Rossendale	2008	3	7	121255810.3	4894.738166
Rossendale	2008	4	8	121250915.6	81.81536912
Rossendale	2009	1	9	121250833.8	1984.267839
Rossendale	2009	2	10	121248849.5	0
Rossendale	2009	3	11	121248849.5	20421.24007
Rossendale	2009	4	12	121228428.3	4.90686344
Rossendale	2010	1	13	121228423.4	973.2556062
Rossendale	2010	2	14	121227450.1	11721.32066
Rossendale	2010	3	15	121215728.8	0
Rossendale	2010	4	16	121215728.8	0.010224932
Rossendale	2011	1	17	121215728.8	12593.44469
Rossendale	2011	2	18	121203135.3	2919.207475
Rossendale	2011	3	19	121200216.1	0
Rossendale	2011	4	20	121200216.1	0
Rossendale	2012	1	21	121200216.1	0
Rossendale	2012	2	22	121200216.1	0
Rossendale	2012	3	23	121200216.1	139.8127833
Rossendale	2012	4	24	121200076.3	8135.733048
Rossendale	2013	1	25	121191940.6	2272.215975
Rossendale	2013	2	26	121189668.4	15.67957498
Rossendale	2013	3	27	121189652.7	587.8849679
Rossendale	2013	4	28	121189064.8	102.5052206
Rossendale	2014	1	29	121188962.3	0.001325417
Rossendale	2014	2	30	121188962.3	14177.29474
Rossendale	2014	3	31	121174785	24926.78626
Rossendale	2014	4	32	121149858.2	4332.048864
Rossendale	2015	1	33	121145526.2	6781.27316
Rossendale	2015	2	34	121138744.9	5609.500598
Rossendale	2015	3	35	121133135.4	342.9067191
Rossendale	2015	4	36	121132792.5	305.3538547
Rossendale	2016	1	37	121132487.1	0
Rossendale	2016	2	38	121132487.1	0
Rossendale	2016	3	39	121132487.1	1394.580405
Rossendale	2016	4	40	121131092.5	0
Rossendale	2017	1	41	121131092.5	20014.2469
Rossendale	2017	2	42	121111078.3	0
Rossendale	2017	3	43	121111078.3	1040.837897
Rossendale	2017	4	44	121110037.5	411.5301219
Rossendale	2018	1	45	121109625.9	5.675264447
Rossendale	2018	2	46	121109620.3	2349.92878
Rossendale	2018	3	47	121107270.3	15536.12665
Rossendale	2018	4	48	121091734.2	3803.498715
Sandwell	2007	1	1	18166363.28	4.586500753
Sandwell	2007	2	2	18166358.69	18952.31769
Sandwell	2007	3	3	18147406.38	29048.77017

Sandwell	2007	4	4	18118357.61	30.63152942
Sandwell	2008	1	5	18118326.97	2960.752341
Sandwell	2008	2	6	18115366.22	15.00868953
Sandwell	2008	3	7	18115351.21	0
Sandwell	2008	4	8	18115351.21	174.6719386
Sandwell	2009	1	9	18115176.54	0
Sandwell	2009	2	10	18115176.54	0
Sandwell	2009	3	11	18115176.54	0
Sandwell	2009	4	12	18115176.54	1252.447701
Sandwell	2010	1	13	18113924.09	0
Sandwell	2010	2	14	18113924.09	119.4960826
Sandwell	2010	3	15	18113804.6	0
Sandwell	2010	4	16	18113804.6	0
Sandwell	2011	1	17	18113804.6	44155.10266
Sandwell	2011	2	18	18069649.49	26483.63262
Sandwell	2011	3	19	18043165.86	113.9298114
Sandwell	2011	4	20	18043051.93	0
Sandwell	2012	1	21	18043051.93	3885.35375
Sandwell	2012	2	22	18039166.58	0
Sandwell	2012	3	23	18039166.58	886.5315618
Sandwell	2012	4	24	18038280.05	18.35713988
Sandwell	2013	1	25	18038261.69	1473.088323
Sandwell	2013	2	26	18036788.6	0
Sandwell	2013	3	27	18036788.6	0.072338182
Sandwell	2013	4	28	18036788.53	784.8998252
Sandwell	2014	1	29	18036003.63	0
Sandwell	2014	2	30	18036003.63	25979.71683
Sandwell	2014	3	31	18010023.91	407.316956
Sandwell	2014	4	32	18009616.6	2284.864587
Sandwell	2015	1	33	18007331.73	0
Sandwell	2015	2	34	18007331.73	734.5349
Sandwell	2015	3	35	18006597.2	0
Sandwell	2015	4	36	18006597.2	40632.14397
Sandwell	2016	1	37	17965965.05	308.8929085
Sandwell	2016	2	38	17965656.16	0
Sandwell	2016	3	39	17965656.16	2219.460955
Sandwell	2016	4	40	17963436.7	11716.64563
Sandwell	2017	1	41	17951720.05	3377.756168
Sandwell	2017	2	42	17948342.3	2045.315967
Sandwell	2017	3	43	17946296.98	2089.941641
Sandwell	2017	4	44	17944207.04	824.9689281
Sandwell	2018	1	45	17943382.07	5.19E-08
Sandwell	2018	2	46	17943382.07	22.62548698
Sandwell	2018	3	47	17943359.44	1.98E-09
Sandwell	2018	4	48	17943359.44	0
Selby	2007	1	1	557107863.5	152144.304
Selby	2007	2	2	556955719.2	5614.0185
Selby	2007	3	3	556950105.2	7089.357387
Selby	2007	4	4	556943015.8	34508.18114
Selby	2008	1	5	556908507.6	19365.11069
Selby	2008	2	6	556889142.5	735.8751225
Selby	2008	3	7	556888406.7	58620.02396
Selby	2008	4	8	556829786.6	138.421137
Selby	2009	1	9	556829648.2	0
Selby	2009	2	10	556829648.2	6.868224571
Selby	2009	3	11	556829641.3	6411.48718
Selby	2009	4	12	556823229.9	0
Selby	2010	1	13	556823229.9	54361.61895
Selby	2010	2	14	556768868.2	0
Selby	2010	3	15	556768868.2	23987.94934
Selby	2010	4	16	556744880.3	1006.051028
Selby	2011	1	17	556743874.2	808.0162143
Selby	2011	2	18	556743066.2	619.8936826
Selby	2011	3	19	556742446.3	25339.84326
Selby	2011	4	20	556717106.5	15028.39412
Selby	2012	1	21	556702078.1	466.4837941
Selby	2012	2	22	556701611.6	988.5961916
Selby	2012	3	23	556700623	5048.447974
Selby	2012	4	24	556695574.6	83813.94286
Selby	2013	1	25	556611760.6	0
Selby	2013	2	26	556611760.6	4542.513544
Selby	2013	3	27	556607218.1	3853.689164
Selby	2013	4	28	556603364.4	7261.367584
Selby	2014	1	29	556596103	44534.09439
Selby	2014	2	30	556551569	39379.15225
Selby	2014	3	31	556512189.8	38958.06642

Selby	2014	4	32	556473231.7	21369.22679
Selby	2015	1	33	556451862.5	170501.1795
Selby	2015	2	34	556281361.3	35568.21035
Selby	2015	3	35	556245793.1	0.008488827
Selby	2015	4	36	556245793.1	13171.2484
Selby	2016	1	37	556232621.9	200458.893
Selby	2016	2	38	556032163	227667.0593
Selby	2016	3	39	555804495.9	3002.352663
Selby	2016	4	40	555801493.6	11119.24121
Selby	2017	1	41	555790374.3	236110.9091
Selby	2017	2	42	555554263.4	23433.16745
Selby	2017	3	43	555530830.2	218745.2525
Selby	2017	4	44	555312085	53203.37589
Selby	2018	1	45	555258881.6	114.557931
Selby	2018	2	46	555258767.1	687.0065573
Selby	2018	3	47	555258080	170856.3607
Selby	2018	4	48	555087223.7	22771.52506
South Bucks	2007	1	1	109057602.8	0
South Bucks	2007	2	2	109057602.8	0.04076619
South Bucks	2007	3	3	109057602.8	292.8007323
South Bucks	2007	4	4	109057310	757.6052568
South Bucks	2008	1	5	109056552.4	9496.628061
South Bucks	2008	2	6	109047055.7	7.116398111
South Bucks	2008	3	7	109047048.6	169.2354073
South Bucks	2008	4	8	109046879.4	12930.66065
South Bucks	2009	1	9	109033948.7	20788.69848
South Bucks	2009	2	10	109013160	10693.1197
South Bucks	2009	3	11	109002466.9	1629.854141
South Bucks	2009	4	12	109000837	0.000935024
South Bucks	2010	1	13	109000837	30017.7895
South Bucks	2010	2	14	108970819.3	1912.53665
South Bucks	2010	3	15	108968906.7	0
South Bucks	2010	4	16	108968906.7	35.31313248
South Bucks	2011	1	17	108968871.4	0
South Bucks	2011	2	18	108968871.4	3202.165329
South Bucks	2011	3	19	108965669.2	0.760184978
South Bucks	2011	4	20	108965668.5	0
South Bucks	2012	1	21	108965668.5	0
South Bucks	2012	2	22	108965668.5	1405.2936
South Bucks	2012	3	23	108964263.2	0
South Bucks	2012	4	24	108964263.2	0
South Bucks	2013	1	25	108964263.2	0
South Bucks	2013	2	26	108964263.2	0
South Bucks	2013	3	27	108964263.2	0.0001
South Bucks	2013	4	28	108964263.2	4640.46985
South Bucks	2014	1	29	108959622.7	825.9833772
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South Bucks	2014	3	31	108954785.9	7261.900804
South Bucks	2014	4	32	108947524	5738.863716
South Bucks	2015	1	33	108941785.2	4723.88903
South Bucks	2015	2	34	108937061.3	4366.705187
South Bucks	2015	3	35	108932694.6	535.1336665
South Bucks	2015	4	36	108932159.4	1063.26668
South Bucks	2016	1	37	108931096.2	0
South Bucks	2016	2	38	108931096.2	60526.58723
South Bucks	2016	3	39	108870569.6	2977.010621
South Bucks	2016	4	40	108867592.6	1940.021251
South Bucks	2017	1	41	108865652.5	0
South Bucks	2017	2	42	108865652.5	1258.803979
South Bucks	2017	3	43	108864393.7	89102.43099
South Bucks	2017	4	44	108775291.3	40.52575473
South Bucks	2018	1	45	108775250.8	8661.791804
South Bucks	2018	2	46	108766589	0
South Bucks	2018	3	47	108766589	0
South Bucks	2018	4	48	108766589	13503.78057
South Gloucestershire	2007	1	1	420702107.1	0
South Gloucestershire	2007	2	2	420702107.1	0
South Gloucestershire	2007	3	3	420702107.1	37532.02661
South Gloucestershire	2007	4	4	420664575.1	89903.65985
South Gloucestershire	2008	1	5	420574671.4	65017.98156
South Gloucestershire	2008	2	6	420509653.4	16605.8718
South Gloucestershire	2008	3	7	420493047.6	15313.09178
South Gloucestershire	2008	4	8	420477734.5	43813.08685
South Gloucestershire	2009	1	9	420433921.4	40656.98474
South Gloucestershire	2009	2	10	420393264.4	810.7494801
South Gloucestershire	2009	3	11	420392453.7	21449.90665

South Gloucestershire	2009	4	12	420371003.7	32252.6047
South Gloucestershire	2010	1	13	420338751.1	207296.1864
South Gloucestershire	2010	2	14	420131455	4379.890948
South Gloucestershire	2010	3	15	420127075.1	6038.21055
South Gloucestershire	2010	4	16	420121036.9	29463.34683
South Gloucestershire	2011	1	17	420091573.5	34316.15305
South Gloucestershire	2011	2	18	420057257.4	81219.73441
South Gloucestershire	2011	3	19	419976037.6	1601.842144
South Gloucestershire	2011	4	20	419974435.8	405.9041425
South Gloucestershire	2012	1	21	419974029.9	8739.98264
South Gloucestershire	2012	2	22	419965289.9	46839.87413
South Gloucestershire	2012	3	23	419918450	3590.637131
South Gloucestershire	2012	4	24	419914859.4	92383.17681
South Gloucestershire	2013	1	25	419822476.2	27084.13811
South Gloucestershire	2013	2	26	419795392.1	113151.5654
South Gloucestershire	2013	3	27	419682240.5	11562.66115
South Gloucestershire	2013	4	28	419670677.8	65632.66274
South Gloucestershire	2014	1	29	419605045.2	5805.661313
South Gloucestershire	2014	2	30	419599239.5	7460.864868
South Gloucestershire	2014	3	31	419591778.6	315300.7167
South Gloucestershire	2014	4	32	419276477.9	56668.50593
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South Gloucestershire	2015	2	34	418963881.4	79005.45813
South Gloucestershire	2015	3	35	418884876	10480.78429
South Gloucestershire	2015	4	36	418874395.2	98860.9838
South Gloucestershire	2016	1	37	418775534.2	51424.24473
South Gloucestershire	2016	2	38	418724110	126803.5
South Gloucestershire	2016	3	39	418597306.5	117315.2228
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South Gloucestershire	2017	1	41	418291960.1	73531.543
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South Gloucestershire	2017	3	43	418122899.1	79743.76604
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South Gloucestershire	2018	2	46	417906776.2	358260.1423
South Gloucestershire	2018	3	47	417548516.1	10270.72583
South Gloucestershire	2018	4	48	417538245.3	384275.1911
South Kesteven	2007	1	1	827088819.6	31014.57363
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South Kesteven	2008	1	5	827013814	20430.50132
South Kesteven	2008	2	6	826993383.5	1110.220082
South Kesteven	2008	3	7	826992273.3	1661.381756
South Kesteven	2008	4	8	826990611.9	627.1538953
South Kesteven	2009	1	9	826989984.7	52038.01163
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South Kesteven	2016	1	37	826432437.9	207834.6093
South Kesteven	2016	2	38	826224603.3	78297.54338
South Kesteven	2016	3	39	826146305.7	111253.2903

South Kesteven	2016	4	40	826035052.4	46447.20734
South Kesteven	2017	1	41	825988605.2	1195.780359
South Kesteven	2017	2	42	825987409.5	21499.75346
South Kesteven	2017	3	43	825965909.7	164697.5889
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South Kesteven	2018	4	48	825731503.6	44632.21757
South Northamptonshire	2007	1	1	594419160.8	3422.258566
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South Northamptonshire	2008	1	5	594369855.6	18290.46955
South Northamptonshire	2008	2	6	594351565.1	0
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South Northamptonshire	2016	1	37	593150523.7	107392.1709
South Northamptonshire	2016	2	38	593043131.6	62974.30898
South Northamptonshire	2016	3	39	592980157.2	56579.5524
South Northamptonshire	2016	4	40	592923577.7	138563.0951
South Northamptonshire	2017	1	41	592785014.6	144334.9048
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South Northamptonshire	2018	2	46	592595834.1	123077.4134
South Northamptonshire	2018	3	47	592472756.7	27738.69134
South Northamptonshire	2018	4	48	592445018	14416.28534
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Taunton Deane	2007	2	2	414377542.8	3602.059054
Taunton Deane	2007	3	3	414373940.7	1804.809857
Taunton Deane	2007	4	4	414372135.9	2014.255755
Taunton Deane	2008	1	5	414370121.6	4841.579001
Taunton Deane	2008	2	6	414365280.1	49167.11453
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Taunton Deane	2008	4	8	414311572.8	3539.098565
Taunton Deane	2009	1	9	414308033.7	7641.43726
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Taunton Deane	2009	3	11	414263181.4	142.3854
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Taunton Deane	2010	3	15	414206555.7	52652.4885
Taunton Deane	2010	4	16	414153903.2	16140.50742
Taunton Deane	2011	1	17	414137762.7	10295.76073
Taunton Deane	2011	2	18	414127466.9	3896.306123
Taunton Deane	2011	3	19	414123570.6	51723.81038

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Taunton Deane	2012	3	23	414019150.9	70138.04726
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Taunton Deane	2015	3	35	413093150.2	17893.00111
Taunton Deane	2015	4	36	413075257.2	85701.16957
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Taunton Deane	2016	4	40	412958957.9	14668.05636
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Taunton Deane	2018	1	45	412607090.4	86902.31988
Taunton Deane	2018	2	46	412520188.1	0
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Taunton Deane	2018	4	48	412520178	17786.04129
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Tendring	2007	3	3	287249310.7	10522.19847
Tendring	2007	4	4	287238788.5	7123.615922
Tendring	2008	1	5	287231664.9	10557.38666
Tendring	2008	2	6	287221107.5	2773.569113
Tendring	2008	3	7	287218333.9	6989.576271
Tendring	2008	4	8	287211344.3	1859.94308
Tendring	2009	1	9	287209484.4	2227.216483
Tendring	2009	2	10	287207257.2	0
Tendring	2009	3	11	287207257.2	7454.577289
Tendring	2009	4	12	287199802.6	21775.81469
Tendring	2010	1	13	287178026.8	9157.747122
Tendring	2010	2	14	287168869	3098.217581
Tendring	2010	3	15	287165770.8	1594.850846
Tendring	2010	4	16	287164176	661.22815
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Tendring	2011	3	19	287050592.1	0
Tendring	2011	4	20	287050592.1	0
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Tendring	2012	3	23	287049808.8	0.0000406
Tendring	2012	4	24	287049808.8	0
Tendring	2013	1	25	287049808.8	0
Tendring	2013	2	26	287049808.8	4226.707374
Tendring	2013	3	27	287045582.1	1227.223154
Tendring	2013	4	28	287044354.8	0
Tendring	2014	1	29	287044354.8	10093.39805
Tendring	2014	2	30	287034261.4	26.42781591
Tendring	2014	3	31	287034235	11643.39665
Tendring	2014	4	32	287022591.6	3434.062939
Tendring	2015	1	33	287019157.5	279.8947575
Tendring	2015	2	34	287018877.6	14933.41675
Tendring	2015	3	35	287003944.2	9395.20944
Tendring	2015	4	36	286994549	143289.1405
Tendring	2016	1	37	286851259.9	135777.3353
Tendring	2016	2	38	286715482.5	21969.16088
Tendring	2016	3	39	286693513.4	44908.85306
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Tendring	2017	3	43	286378803.8	60471.05493
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Tendring	2018	1	45	286251503.1	75522.08571
Tendring	2018	2	46	286175981	316500.6853
Tendring	2018	3	47	285859480.3	85465.91614

Tendring	2018	4	48	285774014.4	85745.60861
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Tower Hamlets	2007	3	3	3665331.32	116.310359
Tower Hamlets	2007	4	4	3665215.01	629.3696283
Tower Hamlets	2008	1	5	3664585.64	2471.997622
Tower Hamlets	2008	2	6	3662113.64	0
Tower Hamlets	2008	3	7	3662113.64	0
Tower Hamlets	2008	4	8	3662113.64	0
Tower Hamlets	2009	1	9	3662113.64	0
Tower Hamlets	2009	2	10	3662113.64	0
Tower Hamlets	2009	3	11	3662113.64	0
Tower Hamlets	2009	4	12	3662113.64	0.02571146
Tower Hamlets	2010	1	13	3662113.61	2389.7708
Tower Hamlets	2010	2	14	3659723.84	741.6263
Tower Hamlets	2010	3	15	3658982.22	8340.144095
Tower Hamlets	2010	4	16	3650642.07	0
Tower Hamlets	2011	1	17	3650642.07	17.64125
Tower Hamlets	2011	2	18	3650624.43	0
Tower Hamlets	2011	3	19	3650624.43	0
Tower Hamlets	2011	4	20	3650624.43	52667.68111
Tower Hamlets	2012	1	21	3597956.75	2164.7925
Tower Hamlets	2012	2	22	3595791.96	128.67125
Tower Hamlets	2012	3	23	3595663.29	12.64923147
Tower Hamlets	2012	4	24	3595650.64	0
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Tower Hamlets	2013	2	26	3595650.64	0
Tower Hamlets	2013	3	27	3595650.64	0.010208
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Tower Hamlets	2014	2	30	3595638.4	3215.173175
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Tower Hamlets	2015	1	33	3590092.66	0
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Tower Hamlets	2015	4	36	3588690.57	228.8422054
Tower Hamlets	2016	1	37	3588461.73	0
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Tower Hamlets	2016	3	39	3587872.98	228.922996
Tower Hamlets	2016	4	40	3587644.05	0
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Tower Hamlets	2017	2	42	3587644.05	0
Tower Hamlets	2017	3	43	3587644.05	0.000201883
Tower Hamlets	2017	4	44	3587644.05	0
Tower Hamlets	2018	1	45	3587644.05	0
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Tower Hamlets	2018	3	47	3574940.85	0
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Warrington	2007	2	2	123986787.6	381820.4788
Warrington	2007	3	3	123604967.1	24157.85197
Warrington	2007	4	4	123580809.3	0.001240514
Warrington	2008	1	5	123580809.3	52903.87934
Warrington	2008	2	6	123527905.4	10263.56133
Warrington	2008	3	7	123517641.8	12784.82618
Warrington	2008	4	8	123504857	60.81809253
Warrington	2009	1	9	123504796.2	0
Warrington	2009	2	10	123504796.2	0
Warrington	2009	3	11	123504796.2	119532.2443
Warrington	2009	4	12	123385263.9	0
Warrington	2010	1	13	123385263.9	0
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Warrington	2010	3	15	123292703	0
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Warrington	2011	1	17	123265451.7	23995.87081
Warrington	2011	2	18	123241455.8	6560.220321
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Warrington	2012	4	24	123183750.9	11.96926792
Warrington	2013	1	25	123183739	623.6022911
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Warrington	2013	4	28	123177451.2	1066.193437
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Warrington	2014	4	32	122605450.4	152422.9986
Warrington	2015	1	33	122453027.4	2774.153593
Warrington	2015	2	34	122450253.2	0.000494776
Warrington	2015	3	35	122450253.2	245.0288399
Warrington	2015	4	36	122450008.2	10793.09929
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Warrington	2017	1	41	122354964.2	54332.89913
Warrington	2017	2	42	122300631.3	0
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Warrington	2018	1	45	121922873.6	1098.326763
Warrington	2018	2	46	121921775.3	65141.84072
Warrington	2018	3	47	121856633.5	0
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Wyre	2007	1	1	246373267.2	12877.04161
Wyre	2007	2	2	246360390.2	0
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Wyre	2008	1	5	246360390.2	4834.647277
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Wyre	2008	3	7	246353957.9	1530.8929
Wyre	2008	4	8	246352427	2581.4957
Wyre	2009	1	9	246349845.5	1143.988644
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Wyre	2009	3	11	246339968.7	2292.238481
Wyre	2009	4	12	246337676.5	881.7784663
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Wyre	2010	2	14	246335463.8	100.66215
Wyre	2010	3	15	246335363.1	369.13555
Wyre	2010	4	16	246334994	858.9438
Wyre	2011	1	17	246334135	22247.63529
Wyre	2011	2	18	246311887.4	9311.384991
Wyre	2011	3	19	246302576	0.000805512
Wyre	2011	4	20	246302576	0
Wyre	2012	1	21	246302576	10208.9033
Wyre	2012	2	22	246292367.1	0.756252534
Wyre	2012	3	23	246292366.3	746.393
Wyre	2012	4	24	246291619.9	150.9058296
Wyre	2013	1	25	246291469	6343.978
Wyre	2013	2	26	246285125.1	4193.884538
Wyre	2013	3	27	246280931.2	8000.255461
Wyre	2013	4	28	246272930.9	1796.112111
Wyre	2014	1	29	246271134.8	8789.044147
Wyre	2014	2	30	246262345.8	4501.618429
Wyre	2014	3	31	246257844.1	3559.683513
Wyre	2014	4	32	246254284.5	27145.8165
Wyre	2015	1	33	246227138.6	0

Table B.2: Kingston upon Hull Q1 2017 - Wyre Q1 2015

Wyre	2015	2	34	246227138.6	38886.6031
Wyre	2015	3	35	246188252	61846.23811
Wyre	2015	4	36	246126405.8	311.0873649
Wyre	2016	1	37	246126094.7	9491.725206
Wyre	2016	2	38	246116603	4738.051992
Wyre	2016	3	39	246111864.9	18642.56695
Wyre	2016	4	40	246093222.4	45196.61021
Wyre	2017	1	41	246048025.8	0.001
Wyre	2017	2	42	246048025.8	40983.10333
Wyre	2017	3	43	246007042.7	8575.615687
Wyre	2017	4	44	245998467	4485.875786
Wyre	2018	1	45	245993981.2	54960.84287
Wyre	2018	2	46	245939020.3	283882.4173
Wyre	2018	3	47	245655137.9	115910.6617
Wyre	2018	4	48	245539227.2	17278.42306

Table B.3: Wyre Q2 2015 - End

B.2 Construction Data

LA.ID	Local.Authority	tot.build	quarter	year	lagged.quarter	lagged year
E07000200	Babergh	80	-1	2006	1	1
E07000200	Babergh	50	0	2006	2	1
E07000200	Babergh	130	1	2007	3	1
E07000200	Babergh	100	2	2007	4	1
E07000200	Babergh	100	3	2007	5	2
E07000200	Babergh	100	4	2007	6	2
E07000200	Babergh	50	5	2008	7	2
E07000200	Babergh	70	6	2008	8	2
E07000200	Babergh	40	7	2008	9	3
E07000200	Babergh	30	8	2008	10	3
E07000200	Babergh	30	9	2009	11	3
E07000200	Babergh	30	10	2009	12	3
E07000200	Babergh	50	11	2009	13	4
E07000200	Babergh	50	12	2009	14	4
E07000200	Babergh	40	13	2010	15	4
E07000200	Babergh	80	14	2010	16	4
E07000200	Babergh	80	15	2010	17	5
E07000200	Babergh	20	16	2010	18	5
E07000200	Babergh	80	17	2011	19	5
E07000200	Babergh	100	18	2011	20	5
E07000200	Babergh	60	19	2011	21	6
E07000200	Babergh	30	20	2011	22	6
E07000200	Babergh	80	21	2012	23	6
E07000200	Babergh	30	22	2012	24	6
E07000200	Babergh	90	23	2012	25	7
E07000200	Babergh	60	24	2012	26	7
E07000200	Babergh	30	25	2013	27	7
E07000200	Babergh	60	26	2013	28	7
E07000200	Babergh	90	27	2013	29	8
E07000200	Babergh	30	28	2013	30	8
E07000200	Babergh	30	29	2014	31	8
E07000200	Babergh	40	30	2014	32	8
E07000200	Babergh	30	31	2014	33	9
E07000200	Babergh	30	32	2014	34	9
E07000200	Babergh	30	33	2015	35	9
E07000200	Babergh	20	34	2015	36	9
E07000200	Babergh	50	35	2015	37	10
E07000200	Babergh	40	36	2015	38	10
E07000200	Babergh	50	37	2016	39	10
E07000200	Babergh	40	38	2016	40	10
E07000200	Babergh	60	39	2016	41	11
E07000200	Babergh	110	40	2016	42	11
E07000200	Babergh	70	41	2017	43	11
E07000200	Babergh	60	42	2017	44	11
E07000200	Babergh	30	43	2017	45	12
E07000200	Babergh	30	44	2017	46	12
E07000200	Babergh	50	45	2018	47	12
E07000200	Babergh	130	46	2018	48	12
E07000200	Babergh	170	47	2018	49	13
E07000200	Babergh	90	48	2018	50	13
E07000027	Barrow-in-Furness	30	-1	2006	1	1
E07000027	Barrow-in-Furness	20	0	2006	2	1
E07000027	Barrow-in-Furness	30	1	2007	3	1
E07000027	Barrow-in-Furness	30	2	2007	4	1
E07000027	Barrow-in-Furness	20	3	2007	5	2
E07000027	Barrow-in-Furness	10	4	2007	6	2
E07000027	Barrow-in-Furness	10	5	2008	7	2
E07000027	Barrow-in-Furness	40	6	2008	8	2
E07000027	Barrow-in-Furness	20	7	2008	9	3
E07000027	Barrow-in-Furness	10	8	2008	10	3
E07000027	Barrow-in-Furness	20	9	2009	11	3
E07000027	Barrow-in-Furness	10	10	2009	12	3
E07000027	Barrow-in-Furness	10	11	2009	13	4
E07000027	Barrow-in-Furness	50	12	2009	14	4
E07000027	Barrow-in-Furness	10	13	2010	15	4
E07000027	Barrow-in-Furness	10	14	2010	16	4
E07000027	Barrow-in-Furness	10	15	2010	17	5
E07000027	Barrow-in-Furness	10	16	2010	18	5
E07000027	Barrow-in-Furness	0	17	2011	19	5
E07000027	Barrow-in-Furness	20	18	2011	20	5
E07000027	Barrow-in-Furness	10	19	2011	21	6

E07000027	Barrow-in-Furness	10	20	2011	22	6
E07000027	Barrow-in-Furness	30	21	2012	23	6
E07000027	Barrow-in-Furness	10	22	2012	24	6
E07000027	Barrow-in-Furness	0	23	2012	25	7
E07000027	Barrow-in-Furness	0	24	2012	26	7
E07000027	Barrow-in-Furness	10	25	2013	27	7
E07000027	Barrow-in-Furness	10	26	2013	28	7
E07000027	Barrow-in-Furness	10	27	2013	29	8
E07000027	Barrow-in-Furness	10	28	2013	30	8
E07000027	Barrow-in-Furness	30	29	2014	31	8
E07000027	Barrow-in-Furness	10	30	2014	32	8
E07000027	Barrow-in-Furness	20	31	2014	33	9
E07000027	Barrow-in-Furness	10	32	2014	34	9
E07000027	Barrow-in-Furness	10	33	2015	35	9
E07000027	Barrow-in-Furness	20	34	2015	36	9
E07000027	Barrow-in-Furness	20	35	2015	37	10
E07000027	Barrow-in-Furness	10	36	2015	38	10
E07000027	Barrow-in-Furness	20	37	2016	39	10
E07000027	Barrow-in-Furness	10	38	2016	40	10
E07000027	Barrow-in-Furness	10	39	2016	41	11
E07000027	Barrow-in-Furness	10	40	2016	42	11
E07000027	Barrow-in-Furness	30	41	2017	43	11
E07000027	Barrow-in-Furness	20	42	2017	44	11
E07000027	Barrow-in-Furness	50	43	2017	45	12
E07000027	Barrow-in-Furness	20	44	2017	46	12
E07000027	Barrow-in-Furness	20	45	2018	47	12
E07000027	Barrow-in-Furness	40	46	2018	48	12
E07000027	Barrow-in-Furness	30	47	2018	49	13
E07000027	Barrow-in-Furness	20	48	2018	50	13
E08000025	Birmingham	460	-1	2006	1	1
E08000025	Birmingham	320	0	2006	2	1
E08000025	Birmingham	600	1	2007	3	1
E08000025	Birmingham	600	2	2007	4	1
E08000025	Birmingham	570	3	2007	5	2
E08000025	Birmingham	590	4	2007	6	2
E08000025	Birmingham	460	5	2008	7	2
E08000025	Birmingham	470	6	2008	8	2
E08000025	Birmingham	450	7	2008	9	3
E08000025	Birmingham	290	8	2008	10	3
E08000025	Birmingham	190	9	2009	11	3
E08000025	Birmingham	290	10	2009	12	3
E08000025	Birmingham	300	11	2009	13	4
E08000025	Birmingham	110	12	2009	14	4
E08000025	Birmingham	230	13	2010	15	4
E08000025	Birmingham	270	14	2010	16	4
E08000025	Birmingham	230	15	2010	17	5
E08000025	Birmingham	140	16	2010	18	5
E08000025	Birmingham	380	17	2011	19	5
E08000025	Birmingham	250	18	2011	20	5
E08000025	Birmingham	140	19	2011	21	6
E08000025	Birmingham	200	20	2011	22	6
E08000025	Birmingham	290	21	2012	23	6
E08000025	Birmingham	170	22	2012	24	6
E08000025	Birmingham	200	23	2012	25	7
E08000025	Birmingham	100	24	2012	26	7
E08000025	Birmingham	240	25	2013	27	7
E08000025	Birmingham	120	26	2013	28	7
E08000025	Birmingham	380	27	2013	29	8
E08000025	Birmingham	130	28	2013	30	8
E08000025	Birmingham	150	29	2014	31	8
E08000025	Birmingham	110	30	2014	32	8
E08000025	Birmingham	160	31	2014	33	9
E08000025	Birmingham	80	32	2014	34	9
E08000025	Birmingham	180	33	2015	35	9
E08000025	Birmingham	180	34	2015	36	9
E08000025	Birmingham	170	35	2015	37	10
E08000025	Birmingham	100	36	2015	38	10
E08000025	Birmingham	180	37	2016	39	10
E08000025	Birmingham	210	38	2016	40	10
E08000025	Birmingham	280	39	2016	41	11
E08000025	Birmingham	160	40	2016	42	11
E08000025	Birmingham	600	41	2017	43	11
E08000025	Birmingham	230	42	2017	44	11
E08000025	Birmingham	200	43	2017	45	12
E08000025	Birmingham	90	44	2017	46	12
E08000025	Birmingham	450	45	2018	47	12

E08000025	Birmingham	390	46	2018	48	12
E08000025	Birmingham	430	47	2018	49	13
E08000025	Birmingham	480	48	2018	50	13
E07000129	Blaby	80	-1	2006	1	1
E07000129	Blaby	60	0	2006	2	1
E07000129	Blaby	120	1	2007	3	1
E07000129	Blaby	110	2	2007	4	1
E07000129	Blaby	50	3	2007	5	2
E07000129	Blaby	50	4	2007	6	2
E07000129	Blaby	20	5	2008	7	2
E07000129	Blaby	40	6	2008	8	2
E07000129	Blaby	20	7	2008	9	3
E07000129	Blaby	20	8	2008	10	3
E07000129	Blaby	10	9	2009	11	3
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E07000129	Blaby	60	13	2010	15	4
E07000129	Blaby	50	14	2010	16	4
E07000129	Blaby	50	15	2010	17	5
E07000129	Blaby	50	16	2010	18	5
E07000129	Blaby	70	17	2011	19	5
E07000129	Blaby	90	18	2011	20	5
E07000129	Blaby	70	19	2011	21	6
E07000129	Blaby	40	20	2011	22	6
E07000129	Blaby	70	21	2012	23	6
E07000129	Blaby	60	22	2012	24	6
E07000129	Blaby	80	23	2012	25	7
E07000129	Blaby	60	24	2012	26	7
E07000129	Blaby	60	25	2013	27	7
E07000129	Blaby	140	26	2013	28	7
E07000129	Blaby	100	27	2013	29	8
E07000129	Blaby	60	28	2013	30	8
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E07000129	Blaby	160	30	2014	32	8
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E07000129	Blaby	140	33	2015	35	9
E07000129	Blaby	250	34	2015	36	9
E07000129	Blaby	160	35	2015	37	10
E07000129	Blaby	140	36	2015	38	10
E07000129	Blaby	140	37	2016	39	10
E07000129	Blaby	180	38	2016	40	10
E07000129	Blaby	150	39	2016	41	11
E07000129	Blaby	130	40	2016	42	11
E07000129	Blaby	130	41	2017	43	11
E07000129	Blaby	140	42	2017	44	11
E07000129	Blaby	110	43	2017	45	12
E07000129	Blaby	130	44	2017	46	12
E07000129	Blaby	60	45	2018	47	12
E07000129	Blaby	110	46	2018	48	12
E07000129	Blaby	120	47	2018	49	13
E07000129	Blaby	60	48	2018	50	13
E07000136	Boston	120	-1	2006	1	1
E07000136	Boston	70	0	2006	2	1
E07000136	Boston	110	1	2007	3	1
E07000136	Boston	100	2	2007	4	1
E07000136	Boston	110	3	2007	5	2
E07000136	Boston	100	4	2007	6	2
E07000136	Boston	40	5	2008	7	2
E07000136	Boston	40	6	2008	8	2
E07000136	Boston	50	7	2008	9	3
E07000136	Boston	30	8	2008	10	3
E07000136	Boston	10	9	2009	11	3
E07000136	Boston	10	10	2009	12	3
E07000136	Boston	70	11	2009	13	4
E07000136	Boston	20	12	2009	14	4
E07000136	Boston	20	13	2010	15	4
E07000136	Boston	130	14	2010	16	4
E07000136	Boston	40	15	2010	17	5
E07000136	Boston	10	16	2010	18	5
E07000136	Boston	80	17	2011	19	5
E07000136	Boston	30	18	2011	20	5
E07000136	Boston	30	19	2011	21	6
E07000136	Boston	20	20	2011	22	6
E07000136	Boston	50	21	2012	23	6

E07000136	Boston	10	22	2012	24	6
E07000136	Boston	40	23	2012	25	7
E07000136	Boston	30	24	2012	26	7
E07000136	Boston	0	25	2013	27	7
E07000136	Boston	40	26	2013	28	7
E07000136	Boston	20	27	2013	29	8
E07000136	Boston	30	28	2013	30	8
E07000136	Boston	30	29	2014	31	8
E07000136	Boston	20	30	2014	32	8
E07000136	Boston	40	31	2014	33	9
E07000136	Boston	50	32	2014	34	9
E07000136	Boston	70	33	2015	35	9
E07000136	Boston	80	34	2015	36	9
E07000136	Boston	40	35	2015	37	10
E07000136	Boston	30	36	2015	38	10
E07000136	Boston	100	37	2016	39	10
E07000136	Boston	40	38	2016	40	10
E07000136	Boston	50	39	2016	41	11
E07000136	Boston	60	40	2016	42	11
E07000136	Boston	60	41	2017	43	11
E07000136	Boston	110	42	2017	44	11
E07000136	Boston	170	43	2017	45	12
E07000136	Boston	70	44	2017	46	12
E07000136	Boston	50	45	2018	47	12
E07000136	Boston	80	46	2018	48	12
E07000136	Boston	50	47	2018	49	13
E07000136	Boston	60	48	2018	50	13
E07000068	Brentwood	20	-1	2006	1	1
E07000068	Brentwood	40	0	2006	2	1
E07000067	Brentwood	80	1	2007	3	1
E07000068	Brentwood	110	2	2007	4	1
E07000068	Brentwood	110	3	2007	5	2
E07000068	Brentwood	50	4	2007	6	2
E07000068	Brentwood	60	5	2008	7	2
E07000068	Brentwood	50	6	2008	8	2
E07000068	Brentwood	10	7	2008	9	3
E07000068	Brentwood	80	8	2008	10	3
E07000068	Brentwood	10	9	2009	11	3
E07000068	Brentwood	20	10	2009	12	3
E07000068	Brentwood	40	11	2009	13	4
E07000068	Brentwood	10	12	2009	14	4
E07000068	Brentwood	40	13	2010	15	4
E07000068	Brentwood	20	14	2010	16	4
E07000068	Brentwood	20	15	2010	17	5
E07000068	Brentwood	10	16	2010	18	5
E07000068	Brentwood	30	17	2011	19	5
E07000068	Brentwood	90	18	2011	20	5
E07000068	Brentwood	80	19	2011	21	6
E07000068	Brentwood	30	20	2011	22	6
E07000068	Brentwood	10	21	2012	23	6
E07000068	Brentwood	0	22	2012	24	6
E07000068	Brentwood	10	23	2012	25	7
E07000068	Brentwood	0	24	2012	26	7
E07000068	Brentwood	10	25	2013	27	7
E07000068	Brentwood	0	26	2013	28	7
E07000068	Brentwood	60	27	2013	29	8
E07000068	Brentwood	10	28	2013	30	8
E07000068	Brentwood	10	29	2014	31	8
E07000068	Brentwood	30	30	2014	32	8
E07000068	Brentwood	10	31	2014	33	9
E07000068	Brentwood	10	32	2014	34	9
E07000068	Brentwood	30	33	2015	35	9
E07000068	Brentwood	30	34	2015	36	9
E07000068	Brentwood	30	35	2015	37	10
E07000068	Brentwood	40	36	2015	38	10
E07000068	Brentwood	10	37	2016	39	10
E07000068	Brentwood	40	38	2016	40	10
E07000068	Brentwood	70	39	2016	41	11
E07000068	Brentwood	10	40	2016	42	11
E07000068	Brentwood	20	41	2017	43	11
E07000068	Brentwood	120	42	2017	44	11
E07000068	Brentwood	230	43	2017	45	12
E07000068	Brentwood	0	44	2017	46	12
E07000068	Brentwood	20	45	2018	47	12
E07000068	Brentwood	60	46	2018	48	12
E07000068	Brentwood	10	47	2018	49	13

E07000068	Brentwood	80	48	2018	50	13
E06000023	Bristol, City of	260	-1	2006	1	1
E06000023	Bristol, City of	290	0	2006	2	1
E06000023	Bristol, City of	220	1	2007	3	1
E06000023	Bristol, City of	340	2	2007	4	1
E06000023	Bristol, City of	400	3	2007	5	2
E06000023	Bristol, City of	380	4	2007	6	2
E06000023	Bristol, City of	370	5	2008	7	2
E06000023	Bristol, City of	280	6	2008	8	2
E06000023	Bristol, City of	200	7	2008	9	3
E06000023	Bristol, City of	260	8	2008	10	3
E06000023	Bristol, City of	200	9	2009	11	3
E06000023	Bristol, City of	200	10	2009	12	3
E06000023	Bristol, City of	190	11	2009	13	4
E06000023	Bristol, City of	210	12	2009	14	4
E06000023	Bristol, City of	170	13	2010	15	4
E06000023	Bristol, City of	260	14	2010	16	4
E06000023	Bristol, City of	270	15	2010	17	5
E06000023	Bristol, City of	140	16	2010	18	5
E06000023	Bristol, City of	270	17	2011	19	5
E06000023	Bristol, City of	190	18	2011	20	5
E06000023	Bristol, City of	260	19	2011	21	6
E06000023	Bristol, City of	130	20	2011	22	6
E06000023	Bristol, City of	300	21	2012	23	6
E06000023	Bristol, City of	240	22	2012	24	6
E06000023	Bristol, City of	190	23	2012	25	7
E06000023	Bristol, City of	120	24	2012	26	7
E06000023	Bristol, City of	350	25	2013	27	7
E06000023	Bristol, City of	160	26	2013	28	7
E06000023	Bristol, City of	210	27	2013	29	8
E06000023	Bristol, City of	220	28	2013	30	8
E06000023	Bristol, City of	170	29	2014	31	8
E06000023	Bristol, City of	270	30	2014	32	8
E06000023	Bristol, City of	350	31	2014	33	9
E06000023	Bristol, City of	140	32	2014	34	9
E06000023	Bristol, City of	250	33	2015	35	9
E06000023	Bristol, City of	220	34	2015	36	9
E06000023	Bristol, City of	130	35	2015	37	10
E06000023	Bristol, City of	110	36	2015	38	10
E06000023	Bristol, City of	150	37	2016	39	10
E06000023	Bristol, City of	210	38	2016	40	10
E06000023	Bristol, City of	170	39	2016	41	11
E06000023	Bristol, City of	160	40	2016	42	11
E06000023	Bristol, City of	180	41	2017	43	11
E06000023	Bristol, City of	140	42	2017	44	11
E06000023	Bristol, City of	250	43	2017	45	12
E06000023	Bristol, City of	190	44	2017	46	12
E06000023	Bristol, City of	140	45	2018	47	12
E06000023	Bristol, City of	170	46	2018	48	12
E06000023	Bristol, City of	280	47	2018	49	13
E06000023	Bristol, City of	170	48	2018	50	13
E07000005	Chiltern	40	-1	2006	1	1
E07000005	Chiltern	50	0	2006	2	1
E07000005	Chiltern	90	1	2007	3	1
E07000005	Chiltern	20	2	2007	4	1
E07000005	Chiltern	10	3	2007	5	2
E07000005	Chiltern	10	4	2007	6	2
E07000005	Chiltern	40	5	2008	7	2
E07000005	Chiltern	40	6	2008	8	2
E07000005	Chiltern	80	7	2008	9	3
E07000005	Chiltern	10	8	2008	10	3
E07000005	Chiltern	10	9	2009	11	3
E07000005	Chiltern	0	10	2009	12	3
E07000005	Chiltern	10	11	2009	13	4
E07000005	Chiltern	20	12	2009	14	4
E07000005	Chiltern	20	13	2010	15	4
E07000005	Chiltern	20	14	2010	16	4
E07000005	Chiltern	50	15	2010	17	5
E07000005	Chiltern	30	16	2010	18	5
E07000005	Chiltern	30	17	2011	19	5
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E07000173	Gedling	40	31	2014	33	9
E07000173	Gedling	20	32	2014	34	9
E07000173	Gedling	30	33	2015	35	9
E07000173	Gedling	30	34	2015	36	9
E07000173	Gedling	20	35	2015	37	10
E07000173	Gedling	50	36	2015	38	10
E07000173	Gedling	20	37	2016	39	10
E07000173	Gedling	80	38	2016	40	10
E07000173	Gedling	10	39	2016	41	11
E07000173	Gedling	60	40	2016	42	11
E07000173	Gedling	40	41	2017	43	11
E07000173	Gedling	30	42	2017	44	11
E07000173	Gedling	140	43	2017	45	12
E07000173	Gedling	60	44	2017	46	12
E07000173	Gedling	50	45	2018	47	12
E07000173	Gedling	60	46	2018	48	12
E07000173	Gedling	90	47	2018	49	13
E07000173	Gedling	40	48	2018	50	13
E07000073	Harlow	10	-1	2006	1	1
E07000073	Harlow	10	0	2006	2	1
E07000073	Harlow	80	1	2007	3	1
E07000073	Harlow	40	2	2007	4	1
E07000073	Harlow	130	3	2007	5	2
E07000073	Harlow	90	4	2007	6	2
E07000073	Harlow	20	5	2008	7	2
E07000073	Harlow	50	6	2008	8	2
E07000073	Harlow	10	7	2008	9	3
E07000073	Harlow	0	8	2008	10	3
E07000073	Harlow	20	9	2009	11	3
E07000073	Harlow	10	10	2009	12	3
E07000073	Harlow	60	11	2009	13	4
E07000073	Harlow	50	12	2009	14	4
E07000073	Harlow	30	13	2010	15	4
E07000073	Harlow	50	14	2010	16	4
E07000073	Harlow	20	15	2010	17	5
E07000073	Harlow	20	16	2010	18	5
E07000073	Harlow	10	17	2011	19	5
E07000073	Harlow	90	18	2011	20	5
E07000073	Harlow	20	19	2011	21	6
E07000073	Harlow	30	20	2011	22	6
E07000073	Harlow	60	21	2012	23	6
E07000073	Harlow	0	22	2012	24	6
E07000073	Harlow	10	23	2012	25	7
E07000073	Harlow	20	24	2012	26	7
E07000073	Harlow	60	25	2013	27	7
E07000073	Harlow	70	26	2013	28	7
E07000073	Harlow	20	27	2013	29	8
E07000073	Harlow	80	28	2013	30	8
E07000073	Harlow	80	29	2014	31	8

E07000073	Harlow	20	30	2014	32	8
E07000073	Harlow	40	31	2014	33	9
E07000073	Harlow	30	32	2014	34	9
E07000073	Harlow	60	33	2015	35	9
E07000073	Harlow	60	34	2015	36	9
E07000073	Harlow	40	35	2015	37	10
E07000073	Harlow	20	36	2015	38	10
E07000073	Harlow	10	37	2016	39	10
E07000073	Harlow	20	38	2016	40	10
E07000073	Harlow	30	39	2016	41	11
E07000073	Harlow	50	40	2016	42	11
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E07000073	Harlow	30	42	2017	44	11
E07000073	Harlow	30	43	2017	45	12
E07000073	Harlow	40	44	2017	46	12
E07000073	Harlow	60	45	2018	47	12
E07000073	Harlow	130	46	2018	48	12
E07000073	Harlow	230	47	2018	49	13
E07000073	Harlow	140	48	2018	50	13
E07000089	Hart	60	-1	2006	1	1
E07000089	Hart	60	0	2006	2	1
E07000089	Hart	100	1	2007	3	1
E07000089	Hart	30	2	2007	4	1
E07000089	Hart	10	3	2007	5	2
E07000089	Hart	10	4	2007	6	2
E07000089	Hart	10	5	2008	7	2
E07000089	Hart	0	6	2008	8	2
E07000089	Hart	0	7	2008	9	3
E07000089	Hart	0	8	2008	10	3
E07000089	Hart	10	9	2009	11	3
E07000089	Hart	0	10	2009	12	3
E07000089	Hart	10	11	2009	13	4
E07000089	Hart	70	12	2009	14	4
E07000089	Hart	20	13	2010	15	4
E07000089	Hart	10	14	2010	16	4
E07000089	Hart	60	15	2010	17	5
E07000089	Hart	30	16	2010	18	5
E07000089	Hart	80	17	2011	19	5
E07000089	Hart	60	18	2011	20	5
E07000089	Hart	40	19	2011	21	6
E07000089	Hart	60	20	2011	22	6
E07000089	Hart	20	21	2012	23	6
E07000089	Hart	110	22	2012	24	6
E07000089	Hart	90	23	2012	25	7
E07000089	Hart	20	24	2012	26	7
E07000089	Hart	70	25	2013	27	7
E07000089	Hart	30	26	2013	28	7
E07000089	Hart	80	27	2013	29	8
E07000089	Hart	70	28	2013	30	8
E07000089	Hart	150	29	2014	31	8
E07000089	Hart	150	30	2014	32	8
E07000089	Hart	120	31	2014	33	9
E07000089	Hart	90	32	2014	34	9
E07000089	Hart	170	33	2015	35	9
E07000089	Hart	50	34	2015	36	9
E07000089	Hart	70	35	2015	37	10
E07000089	Hart	70	36	2015	38	10
E07000089	Hart	90	37	2016	39	10
E07000089	Hart	140	38	2016	40	10
E07000089	Hart	100	39	2016	41	11
E07000089	Hart	190	40	2016	42	11
E07000089	Hart	150	41	2017	43	11
E07000089	Hart	50	42	2017	44	11
E07000089	Hart	30	43	2017	45	12
E07000089	Hart	80	44	2017	46	12
E07000089	Hart	30	45	2018	47	12
E07000089	Hart	60	46	2018	48	12
E07000089	Hart	50	47	2018	49	13
E07000089	Hart	80	48	2018	50	13
E07000062	Hastings	40	-1	2006	1	1
E07000062	Hastings	60	0	2006	2	1
E07000062	Hastings	50	1	2007	3	1
E07000062	Hastings	20	2	2007	4	1
E07000062	Hastings	40	3	2007	5	2
E07000062	Hastings	30	4	2007	6	2
E07000062	Hastings	10	5	2008	7	2

E07000062	Hastings	20	6	2008	8	2
E07000062	Hastings	10	7	2008	9	3
E07000062	Hastings	10	8	2008	10	3
E07000062	Hastings	0	9	2009	11	3
E07000062	Hastings	0	10	2009	12	3
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E07000062	Hastings	40	12	2009	14	4
E07000062	Hastings	0	13	2010	15	4
E07000062	Hastings	10	14	2010	16	4
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E07000062	Hastings	20	17	2011	19	5
E07000062	Hastings	30	18	2011	20	5
E07000062	Hastings	50	19	2011	21	6
E07000062	Hastings	20	20	2011	22	6
E07000062	Hastings	20	21	2012	23	6
E07000062	Hastings	30	22	2012	24	6
E07000062	Hastings	30	23	2012	25	7
E07000062	Hastings	20	24	2012	26	7
E07000062	Hastings	30	25	2013	27	7
E07000062	Hastings	30	26	2013	28	7
E07000062	Hastings	40	27	2013	29	8
E07000062	Hastings	10	28	2013	30	8
E07000062	Hastings	10	29	2014	31	8
E07000062	Hastings	30	30	2014	32	8
E07000062	Hastings	20	31	2014	33	9
E07000062	Hastings	20	32	2014	34	9
E07000062	Hastings	10	33	2015	35	9
E07000062	Hastings	20	34	2015	36	9
E07000062	Hastings	30	35	2015	37	10
E07000062	Hastings	20	36	2015	38	10
E07000062	Hastings	40	37	2016	39	10
E07000062	Hastings	40	38	2016	40	10
E07000062	Hastings	20	39	2016	41	11
E07000062	Hastings	20	40	2016	42	11
E07000062	Hastings	30	41	2017	43	11
E07000062	Hastings	40	42	2017	44	11
E07000062	Hastings	0	43	2017	45	12
E07000062	Hastings	40	44	2017	46	12
E07000062	Hastings	0	45	2018	47	12
E07000062	Hastings	20	46	2018	48	12
E07000062	Hastings	30	47	2018	49	13
E07000062	Hastings	0	48	2018	50	13
E06000019	Herefordshire, County of	140	-1	2006	1	1
E06000019	Herefordshire, County of	90	0	2006	2	1
E06000019	Herefordshire, County of	170	1	2007	3	1
E06000019	Herefordshire, County of	120	2	2007	4	1
E06000019	Herefordshire, County of	110	3	2007	5	2
E06000019	Herefordshire, County of	100	4	2007	6	2
E06000019	Herefordshire, County of	130	5	2008	7	2
E06000019	Herefordshire, County of	130	6	2008	8	2
E06000019	Herefordshire, County of	80	7	2008	9	3
E06000019	Herefordshire, County of	40	8	2008	10	3
E06000019	Herefordshire, County of	90	9	2009	11	3
E06000019	Herefordshire, County of	110	10	2009	12	3
E06000019	Herefordshire, County of	40	11	2009	13	4
E06000019	Herefordshire, County of	30	12	2009	14	4
E06000019	Herefordshire, County of	50	13	2010	15	4
E06000019	Herefordshire, County of	110	14	2010	16	4
E06000019	Herefordshire, County of	50	15	2010	17	5
E06000019	Herefordshire, County of	80	16	2010	18	5
E06000019	Herefordshire, County of	60	17	2011	19	5
E06000019	Herefordshire, County of	80	18	2011	20	5
E06000019	Herefordshire, County of	70	19	2011	21	6
E06000019	Herefordshire, County of	50	20	2011	22	6
E06000019	Herefordshire, County of	60	21	2012	23	6
E06000019	Herefordshire, County of	50	22	2012	24	6
E06000019	Herefordshire, County of	50	23	2012	25	7
E06000019	Herefordshire, County of	60	24	2012	26	7
E06000019	Herefordshire, County of	40	25	2013	27	7
E06000019	Herefordshire, County of	90	26	2013	28	7
E06000019	Herefordshire, County of	50	27	2013	29	8
E06000019	Herefordshire, County of	40	28	2013	30	8
E06000019	Herefordshire, County of	130	29	2014	31	8
E06000019	Herefordshire, County of	370	30	2014	32	8
E06000019	Herefordshire, County of	70	31	2014	33	9

E06000019	Herefordshire, County of	60	32	2014	34	9
E06000019	Herefordshire, County of	130	33	2015	35	9
E06000019	Herefordshire, County of	110	34	2015	36	9
E06000019	Herefordshire, County of	100	35	2015	37	10
E06000019	Herefordshire, County of	50	36	2015	38	10
E06000019	Herefordshire, County of	90	37	2016	39	10
E06000019	Herefordshire, County of	80	38	2016	40	10
E06000019	Herefordshire, County of	160	39	2016	41	11
E06000019	Herefordshire, County of	80	40	2016	42	11
E06000019	Herefordshire, County of	110	41	2017	43	11
E06000019	Herefordshire, County of	180	42	2017	44	11
E06000019	Herefordshire, County of	180	43	2017	45	12
E06000019	Herefordshire, County of	180	44	2017	46	12
E06000019	Herefordshire, County of	190	45	2018	47	12
E06000019	Herefordshire, County of	180	46	2018	48	12
E06000019	Herefordshire, County of	240	47	2018	49	13
E06000019	Herefordshire, County of	100	48	2018	50	13

Table B.4: Babergh - Herefordshire, County of

E06000019	Herefordshire, County of	100	48	2018	50	13
E06000010	Kingston upon Hull, City of	200	-1	2006	1	1
E06000010	Kingston upon Hull, City of	210	0	2006	2	1
E06000010	Kingston upon Hull, City of	250	1	2007	3	1
E06000010	Kingston upon Hull, City of	250	2	2007	4	1
E06000010	Kingston upon Hull, City of	150	3	2007	5	2
E06000010	Kingston upon Hull, City of	250	4	2007	6	2
E06000010	Kingston upon Hull, City of	210	5	2008	7	2
E06000010	Kingston upon Hull, City of	190	6	2008	8	2
E06000010	Kingston upon Hull, City of	160	7	2008	9	3
E06000010	Kingston upon Hull, City of	10	8	2008	10	3
E06000010	Kingston upon Hull, City of	150	9	2009	11	3
E06000010	Kingston upon Hull, City of	10	10	2009	12	3
E06000010	Kingston upon Hull, City of	50	11	2009	13	4
E06000010	Kingston upon Hull, City of	10	12	2009	14	4
E06000010	Kingston upon Hull, City of	90	13	2010	15	4
E06000010	Kingston upon Hull, City of	270	14	2010	16	4
E06000010	Kingston upon Hull, City of	280	15	2010	17	5
E06000010	Kingston upon Hull, City of	120	16	2010	18	5
E06000010	Kingston upon Hull, City of	70	17	2011	19	5
E06000010	Kingston upon Hull, City of	60	18	2011	20	5
E06000010	Kingston upon Hull, City of	140	19	2011	21	6
E06000010	Kingston upon Hull, City of	80	20	2011	22	6
E06000010	Kingston upon Hull, City of	140	21	2012	23	6
E06000010	Kingston upon Hull, City of	190	22	2012	24	6
E06000010	Kingston upon Hull, City of	100	23	2012	25	7
E06000010	Kingston upon Hull, City of	70	24	2012	26	7
E06000010	Kingston upon Hull, City of	90	25	2013	27	7
E06000010	Kingston upon Hull, City of	140	26	2013	28	7
E06000010	Kingston upon Hull, City of	260	27	2013	29	8
E06000010	Kingston upon Hull, City of	500	28	2013	30	8
E06000010	Kingston upon Hull, City of	170	29	2014	31	8
E06000010	Kingston upon Hull, City of	110	30	2014	32	8
E06000010	Kingston upon Hull, City of	50	31	2014	33	9
E06000010	Kingston upon Hull, City of	160	32	2014	34	9
E06000010	Kingston upon Hull, City of	190	33	2015	35	9
E06000010	Kingston upon Hull, City of	170	34	2015	36	9
E06000010	Kingston upon Hull, City of	80	35	2015	37	10
E06000010	Kingston upon Hull, City of	540	36	2015	38	10
E06000010	Kingston upon Hull, City of	80	37	2016	39	10
E06000010	Kingston upon Hull, City of	90	38	2016	40	10
E06000010	Kingston upon Hull, City of	80	39	2016	41	11
E06000010	Kingston upon Hull, City of	230	40	2016	42	11
E06000010	Kingston upon Hull, City of	160	41	2017	43	11
E06000010	Kingston upon Hull, City of	160	42	2017	44	11
E06000010	Kingston upon Hull, City of	230	43	2017	45	12
E06000010	Kingston upon Hull, City of	160	44	2017	46	12
E06000010	Kingston upon Hull, City of	110	45	2018	47	12
E06000010	Kingston upon Hull, City of	150	46	2018	48	12
E06000010	Kingston upon Hull, City of	240	47	2018	49	13
E06000010	Kingston upon Hull, City of	50	48	2018	50	13
E08000035	Leeds	1120	-1	2006	1	1
E08000035	Leeds	880	0	2006	2	1
E08000035	Leeds	1350	1	2007	3	1

E08000035	Leeds	1020	2	2007	4	1
E08000035	Leeds	610	3	2007	5	2
E08000035	Leeds	540	4	2007	6	2
E08000035	Leeds	640	5	2008	7	2
E08000035	Leeds	380	6	2008	8	2
E08000035	Leeds	340	7	2008	9	3
E08000035	Leeds	140	8	2008	10	3
E08000035	Leeds	210	9	2009	11	3
E08000035	Leeds	190	10	2009	12	3
E08000035	Leeds	270	11	2009	13	4
E08000035	Leeds	240	12	2009	14	4
E08000035	Leeds	330	13	2010	15	4
E08000035	Leeds	390	14	2010	16	4
E08000035	Leeds	320	15	2010	17	5
E08000035	Leeds	250	16	2010	18	5
E08000035	Leeds	410	17	2011	19	5
E08000035	Leeds	310	18	2011	20	5
E08000035	Leeds	290	19	2011	21	6
E08000035	Leeds	180	20	2011	22	6
E08000035	Leeds	280	21	2012	23	6
E08000035	Leeds	390	22	2012	24	6
E08000035	Leeds	350	23	2012	25	7
E08000035	Leeds	290	24	2012	26	7
E08000035	Leeds	350	25	2013	27	7
E08000035	Leeds	320	26	2013	28	7
E08000035	Leeds	360	27	2013	29	8
E08000035	Leeds	320	28	2013	30	8
E08000035	Leeds	1120	29	2014	31	8
E08000035	Leeds	390	30	2014	32	8
E08000035	Leeds	420	31	2014	33	9
E08000035	Leeds	560	32	2014	34	9
E08000035	Leeds	400	33	2015	35	9
E08000035	Leeds	390	34	2015	36	9
E08000035	Leeds	460	35	2015	37	10
E08000035	Leeds	300	36	2015	38	10
E08000035	Leeds	320	37	2016	39	10
E08000035	Leeds	480	38	2016	40	10
E08000035	Leeds	600	39	2016	41	11
E08000035	Leeds	300	40	2016	42	11
E08000035	Leeds	1170	41	2017	43	11
E08000035	Leeds	870	42	2017	44	11
E08000035	Leeds	330	43	2017	45	12
E08000035	Leeds	400	44	2017	46	12
E08000035	Leeds	380	45	2018	47	12
E08000035	Leeds	460	46	2018	48	12
E08000035	Leeds	540	47	2018	49	13
E08000035	Leeds	350	48	2018	50	13
E08000022	North Tyneside	100	-1	2006	1	1
E08000022	North Tyneside	80	0	2006	2	1
E08000022	North Tyneside	100	1	2007	3	1
E08000022	North Tyneside	100	2	2007	4	1
E08000022	North Tyneside	60	3	2007	5	2
E08000022	North Tyneside	80	4	2007	6	2
E08000022	North Tyneside	90	5	2008	7	2
E08000022	North Tyneside	30	6	2008	8	2
E08000022	North Tyneside	30	7	2008	9	3
E08000022	North Tyneside	10	8	2008	10	3
E08000022	North Tyneside	80	9	2009	11	3
E08000022	North Tyneside	30	10	2009	12	3
E08000022	North Tyneside	70	11	2009	13	4
E08000022	North Tyneside	50	12	2009	14	4
E08000022	North Tyneside	60	13	2010	15	4
E08000022	North Tyneside	80	14	2010	16	4
E08000022	North Tyneside	80	15	2010	17	5
E08000022	North Tyneside	40	16	2010	18	5
E08000022	North Tyneside	70	17	2011	19	5
E08000022	North Tyneside	90	18	2011	20	5
E08000022	North Tyneside	100	19	2011	21	6
E08000022	North Tyneside	140	20	2011	22	6
E08000022	North Tyneside	100	21	2012	23	6
E08000022	North Tyneside	110	22	2012	24	6
E08000022	North Tyneside	140	23	2012	25	7
E08000022	North Tyneside	40	24	2012	26	7
E08000022	North Tyneside	90	25	2013	27	7
E08000022	North Tyneside	70	26	2013	28	7
E08000022	North Tyneside	80	27	2013	29	8

E08000022	North Tyneside	110	28	2013	30	8
E08000022	North Tyneside	130	29	2014	31	8
E08000022	North Tyneside	180	30	2014	32	8
E08000022	North Tyneside	120	31	2014	33	9
E08000022	North Tyneside	100	32	2014	34	9
E08000022	North Tyneside	90	33	2015	35	9
E08000022	North Tyneside	150	34	2015	36	9
E08000022	North Tyneside	70	35	2015	37	10
E08000022	North Tyneside	120	36	2015	38	10
E08000022	North Tyneside	120	37	2016	39	10
E08000022	North Tyneside	170	38	2016	40	10
E08000022	North Tyneside	240	39	2016	41	11
E08000022	North Tyneside	130	40	2016	42	11
E08000022	North Tyneside	190	41	2017	43	11
E08000022	North Tyneside	230	42	2017	44	11
E08000022	North Tyneside	260	43	2017	45	12
E08000022	North Tyneside	160	44	2017	46	12
E08000022	North Tyneside	70	45	2018	47	12
E08000022	North Tyneside	130	46	2018	48	12
E08000022	North Tyneside	150	47	2018	49	13
E08000022	North Tyneside	100	48	2018	50	13
E07000218	North Warwickshire	60	-1	2006	1	1
E07000218	North Warwickshire	10	0	2006	2	1
E07000218	North Warwickshire	20	1	2007	3	1
E07000218	North Warwickshire	20	2	2007	4	1
E07000218	North Warwickshire	40	3	2007	5	2
E07000218	North Warwickshire	70	4	2007	6	2
E07000218	North Warwickshire	10	5	2008	7	2
E07000218	North Warwickshire	20	6	2008	8	2
E07000218	North Warwickshire	0	7	2008	9	3
E07000218	North Warwickshire	40	8	2008	10	3
E07000218	North Warwickshire	0	9	2009	11	3
E07000218	North Warwickshire	20	10	2009	12	3
E07000218	North Warwickshire	10	11	2009	13	4
E07000218	North Warwickshire	10	12	2009	14	4
E07000218	North Warwickshire	40	13	2010	15	4
E07000218	North Warwickshire	30	14	2010	16	4
E07000218	North Warwickshire	20	15	2010	17	5
E07000218	North Warwickshire	10	16	2010	18	5
E07000218	North Warwickshire	10	17	2011	19	5
E07000218	North Warwickshire	20	18	2011	20	5
E07000218	North Warwickshire	0	19	2011	21	6
E07000218	North Warwickshire	0	20	2011	22	6
E07000218	North Warwickshire	10	21	2012	23	6
E07000218	North Warwickshire	10	22	2012	24	6
E07000218	North Warwickshire	10	23	2012	25	7
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E09000030	Tower Hamlets	960	21	2012	23	6
E09000030	Tower Hamlets	480	22	2012	24	6
E09000030	Tower Hamlets	410	23	2012	25	7
E09000030	Tower Hamlets	70	24	2012	26	7
E09000030	Tower Hamlets	280	25	2013	27	7
E09000030	Tower Hamlets	390	26	2013	28	7
E09000030	Tower Hamlets	460	27	2013	29	8
E09000030	Tower Hamlets	380	28	2013	30	8
E09000030	Tower Hamlets	60	29	2014	31	8
E09000030	Tower Hamlets	210	30	2014	32	8
E09000030	Tower Hamlets	360	31	2014	33	9
E09000030	Tower Hamlets	420	32	2014	34	9
E09000030	Tower Hamlets	960	33	2015	35	9
E09000030	Tower Hamlets	540	34	2015	36	9
E09000030	Tower Hamlets	440	35	2015	37	10
E09000030	Tower Hamlets	300	36	2015	38	10
E09000030	Tower Hamlets	210	37	2016	39	10
E09000030	Tower Hamlets	250	38	2016	40	10
E09000030	Tower Hamlets	210	39	2016	41	11
E09000030	Tower Hamlets	1280	40	2016	42	11
E09000030	Tower Hamlets	120	41	2017	43	11
E09000030	Tower Hamlets	210	42	2017	44	11
E09000030	Tower Hamlets	190	43	2017	45	12
E09000030	Tower Hamlets	350	44	2017	46	12
E09000030	Tower Hamlets	1080	45	2018	47	12
E09000030	Tower Hamlets	170	46	2018	48	12
E09000030	Tower Hamlets	930	47	2018	49	13
E09000030	Tower Hamlets	380	48	2018	50	13

Table B.5: Herefordshire, County of - Tower Hamlets

E09000030	Tower Hamlets	60	29	2014	31	8
E09000030	Tower Hamlets	210	30	2014	32	8
E09000030	Tower Hamlets	360	31	2014	33	9
E09000030	Tower Hamlets	420	32	2014	34	9
E09000030	Tower Hamlets	960	33	2015	35	9
E09000030	Tower Hamlets	540	34	2015	36	9
E09000030	Tower Hamlets	440	35	2015	37	10
E09000030	Tower Hamlets	300	36	2015	38	10
E09000030	Tower Hamlets	210	37	2016	39	10
E09000030	Tower Hamlets	250	38	2016	40	10
E09000030	Tower Hamlets	210	39	2016	41	11
E09000030	Tower Hamlets	1280	40	2016	42	11
E09000030	Tower Hamlets	120	41	2017	43	11
E09000030	Tower Hamlets	210	42	2017	44	11
E09000030	Tower Hamlets	190	43	2017	45	12
E09000030	Tower Hamlets	350	44	2017	46	12
E09000030	Tower Hamlets	1080	45	2018	47	12
E09000030	Tower Hamlets	170	46	2018	48	12
E09000030	Tower Hamlets	930	47	2018	49	13
E09000030	Tower Hamlets	380	48	2018	50	13
E06000007	Warrington	200	-1	2006	1	1
E06000007	Warrington	190	0	2006	2	1
E06000007	Warrington	530	1	2007	3	1
E06000007	Warrington	330	2	2007	4	1
E06000007	Warrington	210	3	2007	5	2
E06000007	Warrington	170	4	2007	6	2
E06000007	Warrington	130	5	2008	7	2
E06000007	Warrington	120	6	2008	8	2
E06000007	Warrington	50	7	2008	9	3
E06000007	Warrington	50	8	2008	10	3
E06000007	Warrington	40	9	2009	11	3
E06000007	Warrington	100	10	2009	12	3
E06000007	Warrington	120	11	2009	13	4
E06000007	Warrington	90	12	2009	14	4
E06000007	Warrington	170	13	2010	15	4
E06000007	Warrington	190	14	2010	16	4

E06000007	Warrington	100	15	2010	17	5
E06000007	Warrington	90	16	2010	18	5
E06000007	Warrington	130	17	2011	19	5
E06000007	Warrington	230	18	2011	20	5
E06000007	Warrington	170	19	2011	21	6
E06000007	Warrington	150	20	2011	22	6
E06000007	Warrington	100	21	2012	23	6
E06000007	Warrington	190	22	2012	24	6
E06000007	Warrington	90	23	2012	25	7
E06000007	Warrington	120	24	2012	26	7
E06000007	Warrington	80	25	2013	27	7
E06000007	Warrington	170	26	2013	28	7
E06000007	Warrington	290	27	2013	29	8
E06000007	Warrington	110	28	2013	30	8
E06000007	Warrington	110	29	2014	31	8
E06000007	Warrington	170	30	2014	32	8
E06000007	Warrington	270	31	2014	33	9
E06000007	Warrington	100	32	2014	34	9
E06000007	Warrington	70	33	2015	35	9
E06000007	Warrington	130	34	2015	36	9
E06000007	Warrington	160	35	2015	37	10
E06000007	Warrington	190	36	2015	38	10
E06000007	Warrington	100	37	2016	39	10
E06000007	Warrington	100	38	2016	40	10
E06000007	Warrington	60	39	2016	41	11
E06000007	Warrington	50	40	2016	42	11
E06000007	Warrington	60	41	2017	43	11
E06000007	Warrington	70	42	2017	44	11
E06000007	Warrington	60	43	2017	45	12
E06000007	Warrington	80	44	2017	46	12
E06000007	Warrington	70	45	2018	47	12
E06000007	Warrington	90	46	2018	48	12
E06000007	Warrington	160	47	2018	49	13
E06000007	Warrington	80	48	2018	50	13
E07000128	Wyre	80	-1	2006	1	1
E07000128	Wyre	40	0	2006	2	1
E07000128	Wyre	70	1	2007	3	1
E07000128	Wyre	50	2	2007	4	1
E07000128	Wyre	70	3	2007	5	2
E07000128	Wyre	40	4	2007	6	2
E07000128	Wyre	60	5	2008	7	2
E07000128	Wyre	40	6	2008	8	2
E07000128	Wyre	40	7	2008	9	3
E07000128	Wyre	40	8	2008	10	3
E07000128	Wyre	10	9	2009	11	3
E07000128	Wyre	20	10	2009	12	3
E07000128	Wyre	30	11	2009	13	4
E07000128	Wyre	20	12	2009	14	4
E07000128	Wyre	40	13	2010	15	4
E07000128	Wyre	0	14	2010	16	4
E07000128	Wyre	30	15	2010	17	5
E07000128	Wyre	80	16	2010	18	5
E07000128	Wyre	40	17	2011	19	5
E07000128	Wyre	40	18	2011	20	5
E07000128	Wyre	70	19	2011	21	6
E07000128	Wyre	30	20	2011	22	6
E07000128	Wyre	30	21	2012	23	6
E07000128	Wyre	10	22	2012	24	6
E07000128	Wyre	40	23	2012	25	7
E07000128	Wyre	20	24	2012	26	7
E07000128	Wyre	20	25	2013	27	7
E07000128	Wyre	50	26	2013	28	7
E07000128	Wyre	80	27	2013	29	8
E07000128	Wyre	20	28	2013	30	8
E07000128	Wyre	110	29	2014	31	8
E07000128	Wyre	40	30	2014	32	8
E07000128	Wyre	70	31	2014	33	9
E07000128	Wyre	30	32	2014	34	9
E07000128	Wyre	40	33	2015	35	9
E07000128	Wyre	90	34	2015	36	9
E07000128	Wyre	90	35	2015	37	10
E07000128	Wyre	60	36	2015	38	10
E07000128	Wyre	110	37	2016	39	10
E07000128	Wyre	140	38	2016	40	10
E07000128	Wyre	130	39	2016	41	11
E07000128	Wyre	90	40	2016	42	11

E07000128	Wyre	110	41	2017	43	11
E07000128	Wyre	40	42	2017	44	11
E07000128	Wyre	80	43	2017	45	12
E07000128	Wyre	100	44	2017	46	12
E07000128	Wyre	60	45	2018	47	12
E07000128	Wyre	70	46	2018	48	12
E07000128	Wyre	120	47	2018	49	13
E07000128	Wyre	60	48	2018	50	13

Table B.6: Tower Hamlets - Wyre

B.3 Segmentation

Year	Time	'Green Space Land Cover Change' (m^2/Ha)	Intervention Code	Lagged Intervention Code	Trend
Q1 2007	1	0.537	0	0	0
Q2 2007	2	0.628	0	0	0
Q3 2007	3	0.350	0	0	0
Q4 2007	4	0.480	0	0	0
Q1 2008	5	0.770	0	0	0
Q2 2008	6	0.274	0	0	0
Q3 2008	7	0.363	0	0	0
Q4 2008	8	0.318	0	0	0
Q1 2009	9	0.341	0	0	0
Q2 2009	10	0.109	0	0	0
Q3 2009	11	0.374	0	0	0
Q4 2009	12	0.351	0	0	0
Q1 2010	13	0.382	0	0	0
Q2 2010	14	0.342	0	0	0
Q3 2010	15	0.314	0	0	0
Q4 2010	16	0.267	0	0	0
Q1 2011	17	0.409	0	0	0
Q2 2011	18	0.359	0	0	0
Q3 2011	19	0.308	0	0	0
Q4 2011	20	0.364	0	0	0
Q1 2012	21	0.532	1	0	1
Q2 2012	22	0.280	1	0	2
Q3 2012	23	0.417	1	0	3
Q4 2012	24	0.328	1	0	4
Q1 2013	25	0.265	1	0	5
Q2 2013	26	0.432	1	0	6
Q3 2013	27	0.430	1	0	7
Q4 2013	28	0.819	1	0	8
Q1 2014	29	0.779	1	1	9
Q2 2014	30	0.695	1	1	10
Q3 2014	31	1.801	1	1	11
Q4 2014	32	0.910	1	1	12
Q1 2015	33	0.880	1	1	13
Q2 2015	34	1.271	1	1	14
Q3 2015	35	0.948	1	1	15
Q4 2015	36	1.040	1	1	16
Q1 2016	37	1.020	1	1	17
Q2 2016	38	1.020	1	1	18
Q3 2016	39	1.210	1	1	19
Q4 2016	40	1.516	1	1	20
Q1 2017	41	1.541	1	1	21
Q2 2017	42	0.842	1	1	22
Q3 2017	43	2.106	1	1	23
Q4 2017	44	1.223	1	1	24
Q1 2018	45	0.835	1	1	25
Q2 2018	46	1.252	1	1	26
Q3 2018	47	1.173	1	1	27
Q4 2018	48	2.084	1	1	28

APPENDIX C

C.1 Segmented Regression Code

```
model_pq <- gls(log(ratio) ~ time + level + levellag +
             trend, method = "ML",
             correlation = corARMA(p = 1, q = 1, form = ~ time),
                 data = gslossratio)
```

C.2 Dynamic Linear Model Code

```
library(tidyr)
library(gdata)
library(plyr)
library(plot.matrix)
library(gridExtra)
library(dlm)
library(nlme)

a1 <- subset(gslossratio, time <= 20)
a1 <- ts(a1$ratio, start = 2007, frequency = 4)

# Model fit to pre-policy period #

# Creating model to test for relevant parameters
mod.build <- function(par) {
  dlmModPoly(1, dV = exp(par[1]), dW = exp(par[2]))
}

# Returns most likely estimate of relevant values for parameters
mle <- dlmMLE(a1, rep(0,2), mod.build);
#nileMLE$conv
if(mle$convergence==0) print("converged")
else print("did not converge")

model1 <- mod.build(mle$par)
# Optimal parameters for model are identified as below
v = V(model1)
w = W(model1)
mod1Filt <- dlmFilter(a1, model1)
```